ASSESSMENT OF AUTONOMOUS VEHICLE SHARING FOR EVACUATION AND DISASTER RELIEF

Final Report

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June 2021

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ACKNOWLEDGMENT

This project was funded by the U.S. Department of Transportation (USDOT) Center for Connected Multimodal Mobility (C^2M^2) (Tier 1 University Transportation Center) Headquartered at Clemson University, Clemson, South Carolina, USA. The authors are grateful for this support.

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Assessment of Autonomous Vehicle Sharing for Evacuation and Disaster Relief		5. Report Date March 2021 6. Performing Organization Code
7. Author(s) Thomas Shirley: ORCID: 0000-0003-2484-8180 Bhavya Padmanabhan: ORCID: 0000-0002-7087-5334 Pamela Murray-Tuite, Ph.D.: ORCID: 0000-0003-3079-289X Nathan Huynh, Ph.D.; ORCID: 0000-0002-4605-5651 Gurcan Comert, Ph.D.; ORCID: 0000-0002-2373-5013 Jiayun Shen: ORCID: 000-0003-4062-2130 Hiwot Tadesse: ORCID: 0000-0001-8157-0221 Treylon Wofford: ORCID: 0000-0002-2285-0378		8. Performing Organization Report No.
9. Performing Organization Name and Address Glenn Department of Civil Engineering Clemson University 210 Lowry Hall, Clemson, SC 29634		10. Work Unit No. 11. Contract or Grant No. 69A3551747117
12. Sponsoring Agency Name and Address Center for Connected Multimodal Mobility (C^2M^2) Clemson University 200 Lowry Hall, Clemson, SC 29634		13. Type of Report and Period Covered Final Report (January 2019 – June 2020) 14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

The goal of this project was to aid emergency management agencies and departments of transportation in preparing for a future hurricane-related mass evacuation where self-driving, autonomous vehicles (AVs) can be utilized to assist with evacuating critical transportation need households (CTNH). A survey was developed and administered to over 1000 residents of South Carolina to capture qualitative assessments of willingness to share their future self-driving AVs in evacuation and disaster relief scenarios. Over 30% of respondents indicated they would be willing or very willing to share their self-driving AVs in these scenarios. Ordered logit models were developed to identify factors associated with this willingness. Statistically significant factors could be categorized into socio-demographics and economics (e.g., unemployed, gender, age, household size), technology adoption and comfort (e.g., use of ride-hailing services, high comfort with using AVs for deliveries), frequency of giving and/or volunteering, and current commute mode.
An ordered logit model for the evacuation scenario was applied to a synthetic South Carolina population to determine the number of AVs that would be shared by the public to assist with evacuation. A Monte Carlo simulation model was developed to test the potential of using only shared AVs to evacuate the CTNH for different scenarios of AV market penetration. The most optimistic scenario predicted that all of the demand could be covered in the not too distant future once AVs start gaining market share. With a 20% AV market penetration, approximately 85% to 90% of the CTNH could be evacuated. Lastly, the experiment results indicated that an AV market penetration of 30% to 35% (depending on the scenario considered) was sufficient to evacuate all CTNH requiring evacuation assistance.

17. Keywords	18. Distribution Statement
Autonomous vehicles; self-driving vehicles; sharing; evacuation; disaster	No restrictions

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	**70**	NA

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EXECUTIVE SUMMARY

This report presents information regarding a future where self-driving, autonomous vehicles (AVs) could be used to assist in hurricane evacuation and disaster relief scenarios. This aid could occur by using privately owned AVs for pre-impact evacuation and post-impact disaster relief. The goal of this project was to aid emergency management agencies and departments of transportation in preparing for a future where self-driving AVs are more common. Toward this goal, the research team explored the public's views on the future use of AVs through focus groups and used these discussions to develop a survey that was administered to over 1000 residents of South Carolina. This survey was used to 1) determine the public's willingness to share their vehicles to assist others with evacuations or to transport disaster relief supplies; 2) identify limitations of this willingness and concerns that could inhibit their willingness; and 3) identify factors associated with a greater willingness to share based on ordered logit models. The ordered logit model for the evacuation scenario was applied to a synthetic population to estimate the number of AVs that would be shared by the public under a given market penetration assumption. This estimate was used with Monte Carlo simulation to determine the percentage of critical transportation need households (CTNH) that could be evacuated.

Based on the survey, over 30 percent of respondents would be willing or very willing to share their self-driving AVs for evacuation or disaster relief. Some limitations individuals would like to impose on this sharing are related to time until hurricane landfall, the length of time a vehicle is away from its owner, and time of day and day of the week the AV is away. Many respondents indicated a preference to be compensated in some way for the AV's use. Over 35 percent would like the ability to track their AVs while under 20 percent would like the ability to travel with the AV.

Based on the ordered logit models, categories of statistically significant factors included socio-demographics and economics, technology adoption and comfort, frequency of giving and/or volunteering, and current commute mode. In the evacuation context, being unemployed and taking regular trips for religious purposes were found to have a positive effect on sharing while being over age 65 and having a household income below $15,000 were found to have a negative effect. For disaster relief, women, age 65+, Pee Dee region (Chesterfield, Marlboro, Dillon, Marion, Horry, Georgetown, Williamsburg, Florence, Williamsburg, Clarendon, Sumter, Lee, and Darlington Counties), and large household respondents were positively associated with willingness to share while having vocational school as the highest education attainment level had negative effects. For technology adoption and comfort, in the evacuation context, greater use of ride-hailing services (eight or more times in a year) and high comfort in using AVs for deliveries and sharing AVs for income in five years were positively associated with sharing. For disaster relief, high comfort in using AVs for deliveries and sharing AVs for income in five years were also positively associated with sharing. In contrast, respondents with few (0-1) social media accounts were negatively associated with sharing in the evacuation context. Giving and volunteering variables positively affecting sharing in the evacuation context were prior experience giving to disaster relief, giving more frequently than annually, and volunteering more frequently than annually. Similarly, respondents who give more frequently than annually as well as those who have experience giving to friends/family in response to a disaster were more willing to share for disaster relief. Finally, commuting by a single-occupancy vehicle had a negative effect on sharing vehicles for disaster relief.

After applying the evacuation ordered logit model to a synthetic South Carolina population, based on Census data, the model showed that approximately 32% of South Carolina citizens were willing to share their AVs to assist with mass evacuation from a major hurricane. Using the Monte Carlo simulation model, the most optimistic scenario predicted that 100% of the demand could be covered in the not too distant future once AVs start gaining market share. It was observed that for market shares (p) less than 20%, the covered demand ratio (CDR) increased linearly with respect to p, and for p greater than 20%, the relationship between CDR and p resembled a

concave function. The logistic regression model generated from the simulation results showed that when p was less than 20%, there was a 5.5% increase in the CDR for each additional 1% increase in p. With a 20% AV market penetration, approximately 85% to 90% of the CTNH could be evacuated. Lastly, the experiment results indicated that an AV market penetration of 30% to 35% was sufficient to evacuate all CTNH requiring evacuation assistance.

This study found that the idea of AV sharing for evacuation and disaster relief to have the potential to improve governmental agencies' response to natural disasters and improve the ability of these agencies to minimize the loss of life associated with these disasters.

CHAPTER 1
Introduction

1.1 Introduction

The southeastern United States has experienced strong hurricanes and flooding over the last few years (e.g., Hurricane Joaquin in 2015 (National Weather Service, 2016); Hurricane Irma in 2017 (Issa et al., 2018); and Hurricane Florence in 2018 (Stewart & Berg, 2019)). One of the impacts of sea-surface temperatures rising is the occurrence of more intense (Hoyos et al., 2006) and more frequent (Saunders & Lea, 2008) hurricanes. In the United States, southeastern and Gulf Coast states are most likely to see the effects of hurricanes, in general, and to encounter this increase in frequency and intensity. As the southeastern region has the largest coastal population growth in the nation (Crossett et al., 2004), the effects of hurricanes will likely become more destructive. In addition, some studies show a decrease in the percentage of Millennials with a driver's license (Dutzik & Baxandall, 2013), which could lead to a greater need for government evacuation assistance in future years.

As a state that experiences hurricanes, South Carolina's Critical Transportation Need Evacuation Operations Plan has specific plans for each County containing an evacuation zone that include locations of shelters, forms of transportation, and estimates of the population needing evacuation assistance. The State estimates close to 50,000 South Carolina residents, would be classified as Critical Transportation Need (CTN) evacuees and require assistance evacuating in a worst-case scenario (SCEMD, 2019). Currently, the evacuation protocol plans for the use of state-owned school buses and transit buses to provide a large part of the transportation of the CTN population to local shelters, supplemented by private motor coaches and, in rural areas, on-demand options (SCEMD, 2019). Similarly, Federal Emergency Management Agency (FEMA) and the American Red Cross, as well as other disaster relief organizations, have plans for the distribution of disaster relief supplies. Typically, these plans consist of storage in mass facilities and delivery using large vehicles (American Red Cross, 2019).

Although advances in technology point toward the adoption of autonomous vehicles (AVs) in the near future, there is little knowledge of their potential for use in these natural disaster situations. This report presents information regarding a future where autonomous vehicles could be used to assist in evacuation and disaster relief scenarios. This aid could occur by using privately owned AVs for pre-impact evacuation and post-impact disaster relief. However, some scholars believe that autonomous vehicles may not be privately owned but owned by corporations or government agencies. Therefore, this research project explores public opinion on these future scenarios, explained in Section 1.1.1, and determines the feasibility of this disaster-based future vehicle sharing system. Specifically, it seeks to answer the research question: what percentage of the CTN population can be evacuated at the predicted level of the public's willingness to share their AVs and at different AV market penetration levels.

1.1.1 Future Autonomous Vehicle Ownership Scenarios

The adoption timeline for AVs in the long term is a topic of debate among researchers. Some research projects anywhere from 25% to 87% adoption of level 4 autonomous vehicles, the lowest level of AV technology able to perform the driving task without a human driver, by 2045 (Bansal & Kockelman, 2017). Others project autonomous vehicles will account for 40-60% of new vehicle sales and 20-40% of the entire vehicle fleet by the 2040s (Litman, 2019). Talebian and Mishra (2018) project anywhere from 15-90% adoption of AVs by 2050, dependent on annual price reductions. All of these studies show a low willingness to pay for autonomous vehicle technology, requiring yearly price decreases to make adoption feasible.

Because of costs, some scholars foresee different ownership scenarios as AVs are adopted. When costs remain too high for the average person to purchase an AV, many studies show vehicle sharing as an implementation option (Litman, 2019; Bansal & Kockelman, 2017). Similarly, some studies show that autonomous micro-transit could be implemented, providing low-cost access to AVs (Fagnant & Kockelman, 2016; Litman, 2019). Micro-transit is defined as a multi-passenger transportation service with dynamically generated routes where people may share pick-up and drop-off points with the purpose of serving as a smaller, more flexible transit-like service (Transportation & National Academies of Sciences, Engineering, and Medicine, 2016). Low-speed micro-transit options have been tested and implemented in some places in Europe as well as cities in the US such as Columbus, Ohio (Scott, 2017, Descant, 2020). Due to uncertainty in the future of AV ownership, a number of future scenarios were designed by the research team and presented to focus groups and survey respondents to determine their future feasibility.

1.2 Goals and Objectives

The goal of this project is to aid emergency management agencies in preparing for a future where self-driving, autonomous vehicles are more common. This goal is pursued through the following objectives:

1. Determine the public's views on the future implementation of autonomous vehicles.
2. Determine the public's willingness to assist others in evacuations and transporting disaster relief supplies by donating their future self-driving, autonomous vehicle's time or experiencing service delays.
3. Identify limitations on this willingness and concerns that could be barriers to donating a vehicle's time or experiencing service delays.
4. Identify factors associated with a greater willingness to donate or experience service delays.
5. Use the predicted level of public willingness to share their AVs to assist with mass evacuation and simulation to determine the percentage of CTN households (CTNH) that can be evacuated at different levels of AV market penetration.

1.3 Intellectual Contribution

This project combines evacuation modeling and future autonomous vehicles. Numerous existing studies explore the potential use and implementation of autonomous vehicles while others identify and optimize strategies for evacuation and disaster relief using current technology. However, little existing work focuses on using this new AV technology in evacuation and disaster relief scenarios. Among those that do exist, Yin et al. (2018) conceived a connected vehicle (CV) application that assists vulnerable households with evacuations while optimizing route guidance to reduce congestion. On the post-disaster side, Mosterman et al. (2014) studied the idea of using a mixed fleet of unmanned ground and aerial vehicles to assist with assessing damage, emergency vehicle routing, and delivery of medical supplies. From the sharing perspective, Wong et al. (2020) found that the sharing economy, specifically the use of shared vehicles and homes, could provide substantial benefits to emergency management personnel in the evacuation of vulnerable populations. Our research project helps to bridge the gap between the existing bodies of work in evacuation modeling and the use of AV technology in disaster situations to determine the feasibility of using shared autonomous vehicles for disaster assistance.

All of this study's data related to the public's perspective has been gathered originally for this project. Data collection instruments that are typical techniques in this type of research, such as focus group sessions and surveys, were developed using existing literature as a base. The data collected was used to create ordered logistic regression models to identify statistically significant characteristics of the population expressing a willingness to share future AVs for both evacuation and disaster relief scenarios. Based on the analysis of these models and the limitations to the population’s willingness to share, the feasibility of an AV sharing system for disasters was determined and these results provide a basis for future research in the field.

1.4 Outline of Report

The remainder of this report is organized into five chapters. Chapter 2 provides a brief overview of literature important to this project such as evacuation modeling and autonomous vehicle implementation while introducing project hypotheses. Chapter 3 provides an overview of the data sources for this report and the process used for reaching the final sample data. The methodology is presented in Chapter 4, which describes the procedure for data analysis. In Chapter 5, the project results are presented and discussed. Finally, in Chapter 6, a project summary is provided as well as conclusions and recommendations for future studies.

CHAPTER 2

Literature Review

2.1 Background

Hurricane evacuation is a complex process where major transportation infrastructure deals with higher demand than any other time. Evacuations of over 1,000 people occur more than three times per month in the United States (Dotson & Jones, 2005). Lives depend on getting people out of an area prior to a disaster as well as supplies into an area after a disaster. With the rise in global temperatures, the intensity and frequency of hurricanes, a major cause of large-scale evacuations, are likely to increase in the future (Broccoli & Manabe, 1990). This means that emergency officials should be constantly working to improve evacuation and disaster relief procedures.

Following the evacuation of an estimated 3 million people for Hurricane Floyd, called the "largest, longest and most incredibly snarled traffic jam ever known" (FEMA, 2000), state transportation departments and other transportation professionals worked to develop new evacuation strategies (Urbina & Wolshon, 2003). Some of these strategies included improving supply through more efficient contra-flow and intelligent transportation systems (ITS) as well as strategies to control demand (Urbina & Wolshon, 2003). Due to computational advances as well as numerous other high-profile disasters such as the events of September 11, 2001, and Hurricane Katrina, this field has grown in interest in recent years (Murray-Tuite & Wolshon, 2013).

Although it is common within the evacuation field to study governmental strategies such as ITS and increased roadway capacity, today, a lot of focus is on the behavioral aspects of evacuation. Survey data is among the most common sources of behavioral data, often focusing on understanding the evacuee decision-making process (Dow & Cutter, 2002; Wong et al., 2018) and specifically, how demographic and household characteristics, as well as institutional decisions, affect risk perception (Dash & Gladwin, 2007; Matyas et al, 2011). Within South Carolina, Hurricane Floyd showed that traffic congestion was a major consideration when evacuating, especially considering that nearly half of evacuees evacuated during the same 6-hour window (Dow & Cutter, 2002).

It has become relatively common for researchers to develop discrete choice models based on data from these surveys to determine what characteristics affect evacuation decisions. Wong et al. (2020) provide an overview of many of these studies. Most often, these models focus on the binary evacuate-stay decision and characteristics of evacuees (Murray-Tuite et al., 2012; Sarwar et al., 2018). However, numerous papers also focus on evacuation departure timing (Fu & Wilmot, 2004; Fu, Wilmot, & Baker, 2006; Urena Cerulle & Cirillo, 2017), shadow evacuation (Yin et al., 2016), destination choice (Cheng et al., 2008), and shelter and mode decisions (Bian et al., 2019) as well as a number of other decisions.

Two topics directly related to this study are shelter type and transportation mode. A recent review of numerous mode choice evacuation studies (Wong et al., 2020) found that an overwhelming majority of evacuees choose to travel by personal vehicle (87-90%) with a majority of others carpooling (2-10%) (Prater et al., 2000; Cheng et al., 2008; Lindell et al., 2011; Wu et al., 2012; Wilmot & Gudishala, 2013; Wu et al., 2013; Wong et al., 2018). However, Bian et al. (2019), using data from two surveys of the largest transit commuting city in the U.S., New York City, found a larger percentage of people taking modes other than driving alone (22% and 41%), with a near-even split between carpooling (8% and 14%) and transit (14% and 16%).

Wong et al. (2020) found anywhere from 44% to 70% of evacuees sheltering with friends and family, followed by 7%-46% staying in hotels/motels and 2%-11% staying in public shelters (Prater et al., 2000; Whitehead, 2000; Smith & McCarty, 2009; Cheng et al., 2011; Lindell et al., 2011; Wu et al., 2012; Wilmot & Gudishala, 2013; Wu et al., 2013; Yin et al., 2014; Wong et al., 2018). However, having to stay in public shelters is often seen as a reason not to evacuate as Wong et al. (2018) showed 31% of non-evacuees from Hurricane Irma chose not to evacuate, in part, due to a refusal to go to a public shelter.

Recently, researchers have studied evacuating the vulnerable population, specifically the carless, elderly, and special needs populations, who are more likely to need assistance in evacuating (Renne, Sanchez, & Litman, 2011; Renne, 2018; Peacock, Morrow, & Gladwin, 2000). Hurricane Katrina in New Orleans is an example of the need for an evacuation plan for those that need assistance leaving prior to a storm. In 2002, the evacuation plan for New Orleans did not consider the carless population, an estimated 200,000 residents (Wolshon, 2002). In the end, many of the city's impoverished, elderly, and carless populations were left in the city to face the brunt of Hurricane Katrina's (2005) effects (Gibbens, 2019; Brunkard, Namulanda, & Ratard, 2008). Even as of 2015/2016, only 13 of America's 50 largest cities had a detailed evacuation plan for carless and vulnerable populations (Renne & Mayorga, 2018). The number of citizens potentially needing evacuation assistance is quite large in some places. A survey of 23 transportation and emergency management agencies estimated that an average of 6-10% of the jurisdiction's population would be classified as special needs, with six agencies estimating this population to be larger than 20% (Wolshon, 2009; Murray-Tuite & Wolshon, 2013). In addition, the US Census Bureau estimates that 8.7% of US households do not have a vehicle readily available for use (US Census Bureau, 2018). Similarly, some studies have shown that younger people are waiting longer to start driving, driving fewer miles, and owning fewer vehicles than previous generations, even when accounting for the economic downturn in the late 2000s (Baxandall, Dutzik, & Inglis, 2014). All of these facts point to the large and likely growing demand for evacuation assistance resources.

In a region where disasters are becoming more frequent, it is becoming more urgent for states to develop better evacuation plans. In South Carolina, the state estimates that a worst-case scenario involving a category 5 hurricane would require approximately 5% of the population residing in evacuation zones, or nearly 49,000 people, to have assistance evacuating (SCEMD, 2019). Typically, the majority of these citizens in need would evacuate using state-owned school buses and city-owned transit buses to local shelters (SCEMD, 2019). However, as discussed above, bus evacuation and evacuation to public shelters are both unpopular and could lead to residents making the dangerous decision not to evacuate (Wong et al., 2018). There are numerous potential reasons for this including the presence of children, elderly, and pets as well as work and financial concerns (Wong et al., 2018).

Evacuating the carless and critical transportation needs (CTN) population is a challenge for governmental organizations. Following Hurricane Irma, Wong et al. (2018) found that government effectiveness was rated lowest for evacuating the carless population, among typical governmental evacuation tasks. An alternative to buses and public shelters that has recently been considered is the use of the sharing economy to assist in transportation (Uber/Lyft) and emergency housing (Airbnb) for evacuees. A recent study concluded that a ride-sharing optimization model could improve evacuation by increasing the capacity of evacuation corridors and reducing traffic congestion (Lu et al., 2020). However, very little research has been done on further uses of the sharing economy and its potential to assist in evacuating the CTN population.

One study looking into this idea was completed in 2020 (Wong et al., 2020). This study found that the sharing economy could potentially provide substantial benefits to problems in emergency management. One potential benefit would be an increase in the number of evacuation resources for vulnerable groups. The study showed that 53.4% of people surveyed would deviate 20 minutes from their route to assist others in evacuating and evacuees are highly willing to assist in transportation before (29.1%) and during the evacuation (23.6%) as well as offering free shelter after the evacuation (19.2%). However, there are a few potential issues with this idea including determining who covers the cost of any resources used, the potential lack of internet access, and congestion effects.

Li et al. (2018) studied the utilization of shared vehicles for emergency evacuation, under no-notice evacuation scenarios with limited time horizons. Numerical simulations were performed to quantify the reduction in the total distance traveled and increase in the number of people evacuated under the proposed evacuation scenario. Naoum-Sawaya and Yu (2017) addressed an evacuation scenario in which evacuating individuals with available room in their vehicles pick up CTN individuals along their routes. The authors proposed a mixed-integer programming model with the objective of maximizing the number of evacuees within a limited amount of time. Two solution methodologies based on Clarke-Wright savings and maximum bipartite matching were proposed, and experiments were conducted to determine the benefits of the proposed evacuation scenario.

In previous years, companies within the sharing economy such as Uber, Lyft, and Airbnb have worked to assist those evacuating for disasters. For example, when Hurricane Florence affected the Carolinas and Virginia in 2018, Uber offered $25 in rides to and from evacuation centers (Rivas, 2018) while Lyft offered $30 credits following the storm (Lyft, 2018). Similarly, Airbnb activated its Open Homes Program where over 600 hosts offered their homes to evacuees for free (Airbnb, 2018; Wong et al., 2020). These companies have assisted in evacuation efforts for a number of other disasters in the past eight years (Wong et al., 2020). More recently, numerous governmental agencies have been looking into the use of the sharing economy due to the potential for evacuations during the COVID-19 pandemic. Florida's Emergency Management Director mentioned the potential use of hotel rooms instead of schools for sheltering, to allow people to distance and minimize the spread of the COVID-19 virus. He also mentioned using Uber and Lyft to transport evacuees instead of mass transportation (Miller, 2020).

With the development of vehicle connectivity and Intelligent Transportation Systems (ITS), many researchers believe that autonomous vehicles will become a common method of transportation in the future (Litman, 2019). Therefore, it is logical to consider their use in the optimization of evacuation and disaster relief scenarios. However, due to cost constraints, many researchers are projecting alternatives to private vehicle ownership in the future (Bansal & Kockelman, 2017). Because of these projections, this study examines scenarios where people share their privately-owned autonomous vehicles for evacuation and disaster relief uses as well as scenarios where companies owning autonomous vehicles increase service times to allow some vehicles to be used for evacuation and disaster relief.

2.2 State of Autonomous Vehicle Technology and Implementation Projections

Autonomous vehicles today account for a negligible share of vehicles on the road. A few cities, such as Columbus, Ohio, and Providence, Rhode Island, are offering low-speed autonomous shuttle service to assist in first-mile/last-mile transportation gaps, and Waymo, owned by Google's parent company, Alphabet, operates around 600 autonomous taxis in Arizona (Boudette, 2019; Descant, 2020). Waymo and numerous other companies are continually testing autonomous vehicle technology across the world. For example, Tesla is using privately-owned vehicles, designed with the ability to travel autonomously in the future, to gain experience in "shadow-mode," a situation where autonomous capabilities are enabled, but the human driver still controls the vehicle (Siddiqui, 2019). Based on the technology improvements, many automakers around the world, including, but not limited to GM, Ford, Honda, and Tesla predict that they will have vehicles capable of self-driving by the early 2020s. These vehicles are likely to be used for ridesharing during their first years (Walker, 2019).

Autonomous vehicles are projected to provide a safer, more efficient transportation system when implemented. According to the National Highway Traffic Safety Administration, approximately 94% of traffic accidents are primarily attributed to driver error (Singh, 2018). By removing human error, autonomous vehicles will decrease vehicle occupant injury and fatality, vehicle damage cost, and insurance costs as well as the congestion and fuel consumption associated with a large portion of traffic accidents (Piao et al., 2016). A Federal Highway Administration (FHWA) report shows that 25% of all congestion is due to traffic incidents on U.S. roadways (Cambridge Systematics, 2004). Autonomous vehicles will also allow for increased productivity, more efficient mobility, decreased stress, and increased mobility options (Greenwald & Kornhauser, 2019; Litman, 2019)

There are a number of major concerns with autonomous vehicle technology today. In 2018 alone, multiple accidents, some including fatalities, occurred due to failures in autonomous vehicle technology. Most notable was a pedestrian fatality where an autonomous Uber struck a pedestrian crossing the street in Tempe, Arizona (Claybrook & Kildare, 2018). In May of 2019, the American Automobile Association (AAA) reported that 71% of Americans would be afraid to ride in a fully autonomous vehicle (AAA, 2019). Outside of safety concerns, costs are a major issue. According to a 2017 study, the average willingness to pay (WTP) for Level 4 automation, the lowest level of automation not requiring a driver, is under $6,000, with almost 60% of people having a WTP of $0. This level of automation was estimated to cost approximately $40,000 in 2015 (Bansal & Kockelman, 2017). This means that either a dramatic increase in WTP or decrease in cost must occur before autonomous vehicle technology becomes mainstream. Other concerns include hardware and software failures, hacking, coordination with human-driven vehicles, increased vehicle travel, risks to bikers and pedestrians, and reduced safety features in these vehicles (Litman, 2019). In addition, AV implementation would require significant spending on maintenance such as pothole removal and striping upkeep as well as ITS improvements such as Vehicle to Infrastructure (V2I) technology (Duvall et al., 2019).

Due to cost concerns, many studies project that autonomous vehicles may be shared when implemented, similar to Uber and other rideshare services (Fagnant & Kockelman, 2015; Piao et al., 2016; Litman, 2019). Today, these rideshare services, also called transportation network companies (TNC's), have developed into a large market, specifically among the young, college-educated, and higher-income (Clewlow & Mishra, 2017). Sharing autonomous vehicles could have a significant impact on urban areas, where it is likely to begin, increasing vehicle miles traveled by around 11% while sizably decreasing emissions (Fagnant & Kockelman, 2014). Some predict that shared autonomous vehicles could produce a viable economic model at as low as $0.45 per mile which is significantly lower than taxi services and convenient for urbanites (Spieser et al., 2014; Gurumurthy, Kockelman, & Loeb, 2019). Today, shared ride-hailing is offered by Uber and Lyft allowing riders traveling to and from similar areas to share rides for a discounted cost. According to Litman (2019), this could be expanded in the future toward autonomous micro-transit. These transit vehicles would carry smaller numbers of people than traditional transit and offer automated transportation at a discounted price (Litman, 2019). In 2020, Marin, California partnered with Uber to have the company run their transit service using Uber's high-occupancy fleet, which will allow riders traveling to the same area to share rides in a form of micro-transit (Mass Transit Magazine, 2020).

As autonomous vehicles are implemented, it is expected that different groups will accept them at different rates. Surveys show that men have a greater willingness than women to use autonomous vehicles (Hohenberger, Spörrle, & Welpe, 2016). Schoettle and Sivak (2014) found that younger people, more educated people, people with full-time employment, and people with more technology in their current vehicle are more interested in having automation technology on their vehicle. A 2014 Pew Research Center report showed that people living in rural areas find the idea of using autonomous vehicles less appealing than those in urban and suburban areas (Smith, Rainie, & Dimock, 2014). Another study shows that older individuals, less educated individuals, and those that enjoy driving are more likely to continue using a regular vehicle over an autonomous vehicle. Interestingly, this study also showed that adults with more children are more likely to choose a shared autonomous vehicle over a traditional vehicle or personally owned AV (Haboucha, Ishaq, & Shiftan, 2017).

Rather than only carrying human occupants, autonomous vehicles are likely to assist in the delivery process in the coming years. In recent years, the sharing economy has developed a new concept known as "crowd-shipping," which is the app-based concept of using personal vehicles to transport goods (Le et al., 2019). These services have taken off, highlighted by delivery services such as UberEats and Postmates (Le & Ukkusuri, 2019). Willingness to allow crowd-sourced shipping is high with 74% of people saying they would be willing to try the idea (Briffaz & Darvey, 2016). Of those willing to act as drivers, young age, male gender, and full-time employment have been shown to be associated with greater willingness to crowd-ship (Punel, Ermagun, & Stathopoulos, 2018).

2.3 Literature Gaps

In reference to autonomous vehicle use in evacuation, very little has been studied. The idea of using autonomous vehicles to assist in the evacuation of carless and limited mobility people was suggested in 2017 (Murray-Tuite et al., 2017). A simulation study looking into the effects of connected and autonomous vehicles (CAV) in contraflow evacuation showed a 12% increase in hourly capacity for a scenario with 20% CAV and a 30% increase in hourly capacity for a scenario with 50% CAV (Ekram & Rahman, 2018). Also, an intersection control algorithm for CAV use during evacuation was designed and evaluated showing significantly less delay than traditionally optimized timing in that scenario (Chang & Edara, 2018). Still, there have not been any studies determining the capabilities of shared autonomous vehicle use for evacuations.

As discussed above, there is a great need for improving the evacuation of vulnerable populations as well as delivering relief supplies to areas where human drivers may not be comfortable traveling. There are only a couple of studies looking into the use of the sharing economy in evacuation (Wong et al, 2020). Similarly, there are only a few studies looking at the use of autonomous vehicles in an evacuation, with most being focused on operations rather than societal acceptance. Yin et al. (2018) conceived a connected vehicle (CV) application that assists vulnerable households with evacuations while optimizing route guidance to reduce congestion. On the post-disaster side, Mosterman et al. (2014) studied the idea of using a mixed fleet of unmanned ground and aerial vehicles to assist with assessing damage, emergency vehicle routing, and delivery of medical supplies. Using existing literature as a base, this study has begun combining autonomous vehicle technologies, the sharing economy, and evacuations/disaster relief. Using the existing projections regarding shared autonomous vehicles (SAV), this study examines the public's view on autonomous vehicle sharing for emergency evacuation scenarios using stated preference survey data.

2.4 Research Hypotheses

To help guide the variables selected for analysis during the rest of the project, the following hypotheses were made. These hypotheses are a supplement to the existing literature highlighted above.

H1: Women are positively associated with willingness to share their vehicles for evacuation and disaster relief.

The effect gender has on giving habits has been well-documented for a number of years. In general, men have been found to be significantly less willing to make donations than women (Eckel & Grossman, 2003). Specifically relating to giving in response to natural disasters, women have been found to be not only more willing to give, but willing to give larger sums (Bergdoll et al., 2019; Eckel, Grossman, & Milano, 2007). Although our study does not specifically ask respondents to donate money, these giving tendencies are notable because our study determines whether people are willing to experience the inconvenience of not having access to a vehicle in order to help others experiencing a dangerous situation.

Another notable reason women could be more willing to share their AVs for disaster assistance would be differences in working and commuting. In South Carolina, women age 20-64 are employed at only 72% compared to nearly 80% for males (US Census Bureau, 2020). With a smaller number of women employed, it can be argued that there are fewer concerns that women may have about vehicle sharing having any disruption on their employment. Similarly, women that do commute typically travel shorter times and distances than men, possibly meaning that more commute options are available (Crane, 2007). A 2001 study found that women are more open to carpooling than men, (Pucher & Renne, 2001) which indicates a willingness to share vehicles. As expected, familial status affects commute lengths for both men and women, with married households indicating longer commutes for men and shorter commutes for women. Similarly, the presence of children has been seen to be related to longer commutes for men (Crane, 2007). However, women typically take more trips per day than men (Kim, Anorve, & Tefft, 2019; McGuckin & Fucci, 2018). Some argue that shorter commutes and more trips per day are due to womens' greater responsibility in caring for children (MacDonald, 1999).

Finally, although a majority of studies have shown men more willing to adopt new autonomous vehicle technologies than women, (Piao et al., 2016; Hohenberger, Spörrle, & Welpe, 2016; Hulse et al., 2018) others have shown the opposite (KPMG, 2013). In regard to the sharing economy, there appears to be little difference in the adoption rates between men and women. However, when giving to crowdfunding sources, one aspect of the sharing economy often studied, women are notably more willing to give to help those in need than men (Smith, 2016).

H2: Older respondents (age 65 and older) are negatively associated with willingness to share their vehicle for disaster assistance.

It is well documented that willingness to adopt new technology decreases as a person ages (Czaja et al., 2006). With autonomous vehicles, this trend continues with older people showing less interest in owning autonomous vehicles than other age groups (Piao et al., 2016; Bansal et al, 2016; Haboucha et al., 2016; Hulse et al., 2018). Similarly, younger people have been shown to use ridesharing services, "crowd-shipping" options, and the sharing economy in general much more than older people (Smith, 2016; Clewlow & Mishra, 2017; Punel, Ermagun, & Stathopoulos, 2018). This points to the idea that older populations are less comfortable with the sharing economy, and likely sharing vehicles, potentially making them less willing to share their vehicles to assist others in disaster scenarios. Regarding transportation, younger populations have lower rates of commuting alone than older people (McKenzie, 2015) and older people typically commute for longer per day (Crane, 2007). Between 2006 and 2013, licensing rates of young people dropped as well, signaling a potential willingness to use alternative modes for traveling (McKenzie, 2015). As sharing a vehicle could result in having to commute via means other than a personal vehicle, this could show that younger people could be more willing to share vehicles.

However, it has been found that giving increases with age in general (Eckel & Grossman, 2003) as well as in response to natural disasters (Eckel, Grossman, & Milano, 2007). This is often attributed to lower incomes and greater financial constraints facing the younger population. Other potential reasons why older populations could be willing to share could be higher rates of social trust, which is the general trust of others (Pew Research Center, 2007), and intuitively, more evacuation experience. Considering all of this, it is still hypothesized that older respondents will be less willing to share their AV for disaster assistance.

H3: Households with evacuation experience are positively associated with willingness to share vehicles for disaster assistance.

Studies show that citizens with direct experience have higher levels of generosity in regard to donating to disaster relief causes (Eckel, Grossman, & Milano, 2007). This is because they likely have more of a connection with the citizens experiencing the natural disaster after experiencing something similar. Similarly, among those who have evacuated, a majority have received assistance from friends or family with either evacuating or sheltering (Wong et al., 2018). Potentially, people with this experience would better understand the fears of those needing assistance due to a natural disaster and may be more willing to assist. Therefore, it seems reasonable to hypothesize that these people would be more willing to share their vehicles for disaster assistance.

H4: Respondents with a higher income (over $100,000 per year) are positively associated with willingness to share their vehicle for disaster assistance.

Income is one factor that often is closely related to donating. In 2012, a study showed that higher income increases the willingness to donate in both planned and unplanned giving scenarios (Brown, Harris, & Taylor, 2012). In 2017-2018, wealthier Americans also donated more often in response to natural disasters than poorer Americans (Bergdoll et al., 2019). These wealthier Americans are shown to have higher levels of social trust than poorer Americans (Pew Research Center, 2007). Understandably, higher-income Americans typically have more disposable income than those with lower income, meaning that any potential risk in sharing is likely perceived as lower. This greater disposable income means they are likely to have more vehicles and new technology, access to the internet and other media, and potentially an earlier adoption of high-cost AVs, all of which make sharing less of a risk.

Individuals with higher incomes also show different commuting patterns than people with lower incomes. Citizens with lower incomes have been found to commute less time per day than those with higher incomes (Besser et al., 2008). Higher-income Americans could have more ability to telecommute, again lowering the negative effects of sharing their vehicle to help those in need (Kontou et al., 2017). Higher-income Americans also show more involvement in the sharing economy (Smith, 2016) as well as ridesharing (Clewlow & Mishra, 2017). All of this points to the idea that these wealthier Americans could be more willing and able to share their vehicles to assist others with natural disasters.

H5: Households with higher education levels (Bachelor's degree or higher) are positively associated with willingness to share their vehicles for disaster assistance.

Numerous studies have shown more educated people are significantly more interested in the adoption of new technologies of all sorts. More educated people adopt technology, in general, earlier than those less educated (Czaja et al., 2006). They have also shown greater willingness to participate in the sharing economy as well as ride-hailing itself (Smith, 2016; Clewlow & Mishra, 2017), meaning they could be more open to sharing an AV to help people in need evacuate or get needed relief supplies. Survey results have found that people with higher education levels are significantly more interested in autonomous vehicle (AV) use as well as AV use through ridesharing services (Piao et al., 2016; Haboucha et al., 2016; Liljamo et al., 2018). Often, more education is associated with higher income, meaning that this group is more likely to have the means to adopt AVs as well.

A study also found that higher education level was associated with a higher level of willingness to donate in planned giving scenarios, such as annual gifts, as well as unplanned scenarios, such as disasters (Brown, Harris, & Taylor, 2012). Similarly, people with higher levels of education have been shown to donate more in response to disasters than those with lower education levels (Bergdoll et al., 2019). Finally, those with higher education levels have been shown to have higher levels of social trust (Pew Research Center, 2007). All of these factors point to the idea that higher education could mean more willingness to share AVs for disaster assistance.

H6: Households with longer commutes are negatively associated with willingness to share a vehicle for disaster assistance.

American cities are significantly more sprawled than most of the rest of the world. In fact, the United States ranked at the bottom of the Demographia World Urban Areas list of the densest urban areas in the world (Demographia, 2019). This sprawl coincides with US automobile dependence as 89% of US trips, over three trillion vehicle miles in 2017, are taken by automobile compared to close to 50% in much of Europe (Lewyn, 2009; Center for Sustainable Systems, 2019; FHWA, 2018). Similarly, the average commute time in the US is 26.6 minutes, one way, and more than 75% of people commute alone (US Census Bureau, 2018). To make matters worse, the average commute in the US has been shown to be lengthening (Crane, 2007). In 2017, the average vehicle was driven just over 10,000 miles annually with miles per year decreasing with vehicle age (McGuckin & Fucci, 2018). Due to this exceptional dependence on motor vehicles, driving habits are likely to impact a person’s willingness to share his/her future autonomous vehicle.

Households with long commutes are typically located further from cities in rural areas. In these areas, personal vehicles are much more necessary than in urban areas due to the lack of travel options and distance from potential attractions. In recent years, workers commuting by automobile decreased for urban/suburban households but increased for rural households (McKenzie, 2015). This shows that rural commuters, typically with longer commutes, are showing less willingness or ability to use modes other than single-occupancy vehicles. Traveling long distances to work indicates a need for automobiles that could reduce the willingness to share vehicles to assist others.

H7: Households with a regular commuting schedule are positively associated with willingness to share their vehicle for disaster assistance.

To some extent, loaning a vehicle requires confidence that one’s vehicle will not be needed while it is away. Households with irregular work schedules are likely less confident that they will not need their personal vehicles for a given time period. Individuals with irregular work schedules have a greater need to have more reliable transportation, meaning that giving that up, even for a day or two to help someone else, could be infeasible.

H8: The number of people in a household is negatively associated with a willingness to share a vehicle for disaster assistance.

People who are married, living with a partner, or divorced travel more than single households (Kim, Anorve, & Tefft, 2019). This could be explained by the presence of children in the home. As children are less likely to be able to drive, parents have more commitments to pick up children and take them places. Similarly, the presence of dependents in a household has been shown to indicate longer commutes (Crane, 2007). These extra travel commitments could decrease parents’ willingness to share vehicles for evacuation and disaster relief. Although a 2006 report found that households with dependent children are expected to give more than those without (Schokkaert, 2006), donation experience may not be applicable when discussing families.

This is because the presence of dependents provides more opportunity for unplanned vehicle needs that many families may be uncomfortable with.

H9: Respondents' trust and adoption of technology is associated with willingness to share a vehicle. This is tested by hypothesizing that H9a) ownership of a vehicle with a high number of recent innovations and H9b) a high number of ride-hailing service uses in the past year is positively associated with willingness to share vehicles for disaster assistance and H9c) a low number of social media accounts is negatively associated with willingness to share their vehicles for disaster assistance.

AV technology today is not the most popular. AAA (2019) reported that 71% of Americans would be afraid to ride in a fully autonomous vehicle. People are concerned with numerous aspects of the technology such as safety and privacy. However, there is reason to believe that this technology will become more accepted in the near future, starting with those who trust and use technology today. A 2016 study found the individuals claiming a high interest in new technology are significantly more likely to adopt AVs (Bansal et al 2016; Haboucha et al., 2016).

H10: Households that H10a) give and H10b) volunteer more are positively associated with a willingness to share a vehicle for disaster assistance.

Americans are generous with their giving, with around 70% of households giving each year at an average of 1.7% of their yearly income (Wright, 2002). Similarly, according to a 2018 report, approximately 50% of North American donors give in response to natural disasters (Nonprofit Tech for Good, 2019). For a project discussing sharing vehicles, it is crucial to look into the giving tendencies of different groups in society. These giving tendencies are likely to affect the groups that would be willing to share their autonomous vehicles and what limitations they would place on their willingness to give. One of the most well-known donation programs in the US is the Organ Donor program. This program, allowing citizens to donate organs after passing away or before passing in rare circumstances, contains registrations from around 58% of US adults (USDHHS, 2019).

According to a report by Indiana University Lilly Family School of Philanthropy at IUPUI, approximately 30% of American households made a disaster-related donation in 2017 or 2018 (Bergdoll et al., 2019). Multiple studies have shown that those who make more charitable donations as a whole are more likely to donate to a disaster relief cause (Eckel, Grossman, & Milano, 2007; Brown, Harris, & Taylor, 2012; Bergdoll et al., 2019). All of this information points to the idea that households that give and volunteer more will be more willing the share their vehicle to assist others with disasters.

H11: Regular religious activity is positively associated with a willingness to share a vehicle for disaster assistance.

Religious activity has been shown to be very influential in donation studies in the past. A 2012 study showed more religious activity increases the willingness to donate in both planned and unplanned scenarios (Brown, Harris, & Taylor, 2012). Similarly, a 2003 study by Eckel and Grossman found that higher attendance at religious services is a positive factor for giving. Religion and giving are often considered intertwined, with faith institutions being a major recipient of donations in the US (Wright, 2002).

H12: Residing in urban areas is positively associated with a willingness to share a vehicle for disaster assistance.

Similar to commuting, people choosing to live in an urban environment have been found to have a number of characteristics that could potentially make them more willing to share autonomous vehicles for evacuation assistance and disaster relief distribution. First, urbanites have been found to be more likely to adopt AVs in some form than those residing in rural areas (Bansal et al, 2016; Liljamo et al., 2018). As discussed above, these autonomous vehicles could be privately owned or shared. Continuing, people residing in urban areas have been found to be more active in the sharing economy (Smith, 2016). In regard to commuting, urban residents typically commute shorter distances (Crane, 2007) and, intuitively, have more viable transportation options such as walking, biking, and transit. Having more transportation options reduces the dependence on the automobile and it is hypothesized that this will make urbanites more willing to share autonomous vehicles for disaster purposes.

CHAPTER 3

Data

3.1 Data Acquisition and Preparation

One of the most crucial aspects of any survey-based modeling is the careful process of writing the survey. When in the exploratory stages of a new area of study, focus group sessions can be used to determine the general public's attitudes, beliefs, and experiences relating to that topic (Gibbs, 1997). As a way to begin to understand the public's ideas on autonomous vehicle implementation and factors involved in willingness to share, the research team held three 90-minute focus groups in the state of South Carolina, hosting one session at Clemson University in September of 2019 and two sessions at the University of South Carolina in December of 2019. These focus groups drew a total of 31 participants consisting mostly of students as well as professionals and members of the general public. The majority of participants were between 18 and 24; however, the research team made sure to include a number of parents. The research team structured focus groups to specifically explore topics such as:

- Public trust of new recent innovations in-vehicle technology such as adaptive cruise control and emergency automatic braking as well as comfort with ride-hailing services;
- Evacuation and other natural disaster experiences;
- Viability of four potential AV implementation scenarios (little AV adoption, private ownership and sharing vehicles for income, subscription AV service adoption, and micro-transit AV adoption); and
- Willingness to share AVs for evacuation and disaster relief and limitations of this willingness based on the implementation scenarios.

The four AV implementation scenarios, based on existing literature are described below:

1. Little AV Adoption – In this future, AVs have not made the impact many scholars expect, and instead, most people continue to use human-controlled vehicles with some automated features.
2. Purchase and Share – In this future scenario, human-controlled vehicles are replaced by autonomous vehicles. However, due to high costs, vehicle owners share these vehicles when not in use to earn income. This future scenario offers people the comfort of owning a vehicle while giving up constant access. A variant of this future that was also presented in this project includes sharing with only family and friends.
3. Subscription Rideshare – In this future scenario, drivers give up their personal vehicle for autonomous rideshare programs. This scenario, aimed at people living in cities, allows people to purchase a subscription with a certain number of rides over a given time period as their primary way to travel.
4. Micro-transit – In this future scenario, drivers make the choice to take autonomous micro-transit for regular trips. This service picks up passengers traveling to and from the same area and drops them off. This scenario offers the lowest cost option for people desiring to access autonomous vehicle technology (Litman, 2019).

In reviewing the focus group discussions, the research team determined that participants had more trouble envisioning future number 2 and number 4 above, and therefore, they were not included in the final survey. Among the greatest concerns with autonomous vehicles as a whole was coordination with human drivers, insurance and liability, and cost, while participants liked the convenience associated with AVs. In regard to AV use in evacuation and disaster relief, participants showed the most concern about insurance/liability of vehicles and cited having friends and family in an area as an important factor in sharing.

Based on the focus group transcript review as well as a review of existing literature, a survey was drafted. As the future of autonomous vehicles is a subject for which not all Americans are knowledgeable, the research team pretested the survey with a diverse group of individuals, ranging from age 20 to age 85 with a variety of racial, occupational, and familial backgrounds to ensure that it would be understood by all participants. Based on the comments from three rounds of pretesting, the survey was modified for final use. The final survey contained sections on the following topics:

- Existing commuting and travel habits
- Vehicle technology
- General technology
- Sharing economy
- Volunteering and giving
- Natural disaster experience
- Autonomous vehicles
- Private ownership evacuation (Given to 50% of survey respondents)
- Private ownership disaster relief (Given to 50% of survey respondents)
- Subscription ride-hailing
- Subscription ride-hailing disaster scenario
- Demographics

The survey data was collected via Qualtrics' survey software, which is an online survey platform designed to allow researchers to implement skip-patterns and tailored question orders. This helps to create a more efficient survey process (Qualtrics, 2020). The research team chose to implement skip patterns under numerous scenarios, typically to shorten the survey for people without experience with certain topics such as evacuation, commuting, or vehicle technology. Although skip patterns shorten the survey for respondents, they also decrease the number of responses for numerous variables, complicating analysis. To achieve a final average survey duration with outliers removed of 15 minutes, the research team chose to split the sample in half and show respondents only one of the evacuation or disaster relief scenarios.

Qualtrics research panels, which are a representative group of participants from desired demographic groups recruited to respond to a survey, were used to obtain survey results (Qualtrics, 2020). The responses were limited to 1,050 households from within the state of South Carolina. Using estimates from the US Census Bureau, the research team chose to implement the demographic quotas shown in Table 3.1. The team chose to adjust the quotas by slightly oversampling younger and higher-income respondents. This was done because our research scenario is unlikely to occur in the next 10 years and because autonomous vehicles will likely be too expensive for many low and middle-income households when first deployed (Litman, 2019).

The research team decided against weighting the data for a number of reasons. First, outside of intentionally oversampled demographics, age, and income, the only other demographic notably different from American Community Survey (ACS) South Carolina estimates was education, as our sample was overeducated. Due to the significant majority of demographics matching South Carolina estimates, the research team decided that the weighting process was unlikely to significantly improve survey analysis results.

Table 3.1: Demographic Quota Comparisons

Demographic	Choices	Survey %	Census %
Gender:	Male	49.0%	48.6%
	Female	51.0%	51.4%
Race:	White/Caucasian	67.0%	67.0%
	Black/African American	26.6%	26.6%
	Asian	2.0%	1.6%
	American Indian, Pacific Islander, or Other	2.4%	2.4%
	Two or more races	2.0%	2.4%
Hispanic:	Yes	6.0%	5.8%
	No	94.0%	94.2%
Age*:	18-34	29.1%	28.3%
	35-54	36.4%	31.8%
	55+	34.5%	39.9%
Income:	Less than $50,000	30.0%	47.5%
	$50,000-$100,000	41.5%	31.1%
	$100,000-$200,000	22.4%	16.8%
	Over $200,000	6.1%	4.6%

* Census % redistributed to account for age 18+ survey sample
Source: 2018 ACS 1-year estimates

When reviewing the sample data, the research team implemented a number of checks to ensure that all data used in the analysis was acceptable. First, when the survey was deployed through Qualtrics, the research team included three quality check (QC) questions with correct responses given in the question. An example from the survey is “Please select “Strongly Agree” here.” If respondents failed two of the three QC questions, their survey was terminated. After receiving survey results, the team removed 36 responses from the data used in the final models for failing additional checks such as having more household dependents than household members.

Throughout the analysis, numerous dummy variables were created to test for the presence of certain characteristics within the sample. Binary dummy variables are commonplace in survey data analysis today and allow researchers to better understand the effects of categorical variables (Garavaglia & Sharma, 2016). For variables with real numerical meaning, such as income or number of social media accounts, these values were recoded as semi-continuous variables based on the midpoint of each data category as is also common in survey data analysis (Javaras & Van Dyk, 2003).

This survey aimed to determine public views on the future of autonomous vehicles, factors associated with greater willingness to share vehicles for disaster relief, and limitations on vehicle sharing. To determine public input on the future disaster scenarios that do not exist today, the team created evacuation and disaster relief scenarios for use in the survey. The survey was drafted in the stated preference (SP) style, an idea which has received some criticism for misrepresenting public views on novel topics, but is commonly used in research today (Brownstone, Bunch, & Train, 2000). The research team implemented a Likert-type format for all questions regarding the intensity of feeling related to a specific topic. Although some studies argue that this data could be analyzed as continuous data (Harpe, 2015), the research team decided that the survey format selected did not allow for Likert analysis as continuous data. Specifically, this was due to the visual display of Likert-type questions without specification of equal intervals and the inability to combine multiple Likert-type questions into a Likert scale. Numerous studies caution that the improper use of Likert-Type data could lead to researchers coming to incorrect conclusions (Jamieson, 2004; Harpe, 2005; Bishop & Herron, 2015). Finally, this survey was deployed during the COVID-19 global pandemic in April/May of 2020 and researchers chose to direct questions at each respondent’s lifestyle prior to the pandemic.

Prior to analysis, the evacuation and disaster relief willingness to share variables were condensed from seven to five ordered categories combining extremely willing/willing and extremely unwilling/unwilling. This was done after deciding that the ordered logit approach would be used, rather than a continuous approach, as some studies mention the use of linear regression, which was deemed inappropriate for this study, for ordinal variables with a large number of categories (Ward & Ahlquist, 2018). Notably, this combination of categories has no effect on the middle three categories not involved in the merge (Norusis, 2005). This left the research team with willing, somewhat willing, neither willing nor unwilling, somewhat unwilling, and unwilling categories. Table 3.2 shows the original distributions of willingness to share for both evacuation and disaster relief. This table shows that there is little difference between respondents' willingness to share for either scenario. To confirm this, the responses were compared for the two samples using the Mann-Whitney U Test, and no significant differences were found. The results of this test are shown in Appendix B.

Table 3.2: Willingness to Share Variable Distribution

	Evacuation (n=525)	Disaster Relief (n=525)
Extremely willing	81 (15%)	66 (13%)
Willing	112 (21%)	132 (25%)
Somewhat willing	121 (23%)	135 (26%)
Neither willing nor unwilling	50 (10%)	48 (9%)
Somewhat unwilling	36 (7%)	30 (6%)
Unwilling	50 (10%)	40 (8%)
Extremely unwilling	75 (14%)	74 (14%)

Table 3.3 presents summary statistics of the variables considered for the final models. Table 3.4 presents the correlation data for each variable included in the final analysis.

To determine whether the proportion of each sample demographic and significant variables were similar between the evacuation and disaster relief groups, chi-square tests were performed using SPSS. For most characteristics, no significant differences in the samples were determined. However, based on these tests, the evacuation sample had a significantly greater ($p<.05$) proportion of respondents with a high number of technology features on their newest vehicle and a high number of part-time employees. The evacuation sample also had a somewhat significantly ($p<.1$) greater number of unemployed, more giving, and suburban respondents while the disaster relief sample had a somewhat significantly ($p<.1$) greater number of urban respondents. The results of these tests are shown in Appendix B.

Table 3.3: Summary Statistics of Selected Variables

Variable	Number of responses	Min.	Max.	Mean	Standard Deviation
Dependent Variables					
Willingness to share AV for evacuation	518	1	5	3.41	1.60
Willingness to share AV for disaster relief support	511	1	5	3.50	1.57
Independent Variables					
Demographics					
Gender – Women	1050	0	1	0.51	0.50
High income (>$100,000 per year)	1050	0	1	0.28	0.45
Household size	1039	1	5	2.70	1.19
Educated with a 4 year degree or more	1050	0	1	0.50	0.50
Highest education of vocational/technical school	1050	0	1	0.04	0.19
Age 65 or older	1050	0	1	0.18	0.38
Income under $15,000 per year	1050	0	1	0.09	0.28
Unemployed	1050	0	1	0.06	0.24
Takes religious trips during a typical week	1050	0	1	0.33	0.47
Living in Pee Dee region of South Carolina**	1050	0	1	0.19	0.39
Living in urban area	1050	0	1	0.13	0.33
Technology					
Use of ride-hailing services 8+ times in past year	1050	0	1	0.16	0.37
0 or 1 social media accounts	1050	0	1	0.23	0.42
High comfort in AV deliveries in 5 years	1050	0	1	0.49	0.50
High comfort in sharing AV for income in 5 years	1050	0	1	0.10	0.30
High number of technology features on newest vehicle	1008	0	1	0.13	0.34
Evacuation/Disaster Relief Experience					
Household evacuation experience	1050	0	1	0.33	0.47
Experience evacuating with friends/family	345	0	1	0.15	0.36
Received evacuation assistance from friends/family	345	0	1	0.32	0.47
Giving and Volunteering					
Giving to charitable causes more than once per year	1050	0	1	0.61	0.49
Volunteering more than once per year	1050	0	1	0.49	0.50
Experience giving any disaster relief assistance	1050	0	1	0.63	0.48
Experience giving to assist friends/family in disaster relief efforts	1050	0	1	0.25	0.43
Commuting					
Commuting by single-occupancy vehicle	663	0	1	0.81	0.39
Commute length*	648	10	60	22.61	13.43
Regular weekly commute schedule	663	0	1	0.71	0.46

*Does not include respondents that did not have a regular commute
** Description of Pee Dee region located in Appendix C

Table 3.4: Correlation Matrix of Independent Variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1	Female8	1.00																									
2	HighInc5	-.04	1.00																								
3	HHSize2	.07*	-0.04	1.00																							
4	HighlyEdu5	-.12**	.33**	-.12**	1.00																						
5	EduTech5	.10**	-.08*	0.01	-.19**	1.00																					
6	O65	-.13**	.25**	-.30**	.13**	.07*	1.00																				
7	U15k8	.12**	-.19**	-0.00	-.22**	-.01	-.13**	1.00																			
8	StatusUnemp1	.08*	-.13**	.07*	-.16**	.06	-.09**	.26**	1.00																		
9	Religious1	.02	.07*	-.00	.11**	-.03	.00	-.10**	-.08**	1.00																	
10	PeeDee5	.02	-.03	-.04	-.05	.02	.03	.04	.06	-.02	1.00																
11	Urban5	.02	-.08*	-.06	-.02	.00	-.05	.13**	-.03	-.01	-.01	1.00															
12	RHO8	-.09**	.05	-.02	.06	-.03	-.13**	.04	-.06	-.03	-.01	.13**	1.00														
13	LowSM5	-.14**	.08**	-.16**	.00	.03	.30**	-.05	-.02	-.03	.02	-.07*	-.11**	1.00													
14	HAVDelivery5	-.14**	.02	.05	.09**	-.01	-.03	-.06*	-.04	.03	.08*	-.00	.14**	-.10**	1.00												
15	HAVShareInc5	-.09**	-.08**	.04	-.04	.00	-.13**	.04	-.01	-.06	.04	.08*	.17**	-.12**	.26**	1.00											
16	HighTechVeh8	.01	.27**	.01	.03	.00	.15**	-.04	-.02	-.01	.03	-.05	.03	.05	.05	.02	1.00										
17	EvacExp5	-.03	.08**	-.01	.05	.03	.03	-.07*	-.06	-.00	.13**	.01	.14**	-.05	.07*	.02	.04	1.00									
18	EvacFF8	.05	-.11*	-.02	-.15**	.07	-.12*	.25**	.12*	-.01	.01	.10	.16**	-.06	.04	.19**	-.03	.	1.00								
19	FamFrndAssist8	.12*	-.07	.31**	-.05	-.09	-.22**	.01	.08	-.02	-.08	.02	.16**	-.27**	.08	.08	.05	.	.22**	1.00							
20	MOftGive5	-.07*	.21**	-.06	.27**	.01	.14**	-.18**	-.17**	.23**	.01	-.08*	.08**	-0.02	.12**	-.01	.05	.05	-.01	.06	1.00						
21	MOftVol5	.02	.12**	0.05	.16**	-.04	-.00	-.11**	-.12**	.28**	-.03	-.05	.11**	-.13**	.16**	.10**	0.02	.12**	-.06	.11*	.39**	1.00					
22	GiveDR	.03	.15**	.05	.17**	-.01	-.02	-.16**	-.13**	.14**	.02	-.03	.14**	-.16**	.16**	0.04	.07*	.14**	.05	.27**	.31**	.30**	1.00				
23	GiveDRFam1	.07*	.02	.08**	.01	.02	-.10**	-.04	-.03	-.00	.06*	.02	.05	-.17**	.07*	.02	.04	.13**	.11*	.20**	.06	.16**	.44**	1.00			
24	DriveAlone8	-.10**	.09*	-.13**	.15**	-.04	.06	-.18**	-.10*	.02	.03	-.08*	-.16**	.07	-.08*	-.07	-.01	-.03	-.25**	-.30**	.06	-.02	-.03	-.11**	1.00		
25	CommuteLength5	-.10**	.06	.00	.14**	.03	.02	-.04	-.01	.01	-.06	-.05	.02	.08*	-.02	.00	.03	.03	-.06	-.06	.07	.01	.04	-.00	.02	1.00	
26	RegCommute8	-.05	-.00	.01	.03	-.00	-.06	-.08*	.03	.10*	-.10*	.03	-.11**	.06	.01	.02	.06	-.08*	-.06	-.02	-.08	.01	-.04	-.06	.08*	0.01	1.00

* Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

3.2 Limitations of Vehicle Sharing

In addition to the creation of discrete choice models, the associated survey asked numerous questions to better understand the public's concerns and limitations associated with sharing an autonomous vehicle for evacuation or disaster relief. As discussed above, half of the survey respondents received each of the evacuation and disaster relief scenarios, while all respondents received the subscription rideshare scenario. It is very important to understand that the willingness to share is bound by a number of restrictions. An overview of these limitations is shown in Table 3.5.

Table 3.5: Limitations on Willingness to Share

	Evacuation	**Disaster Relief**	**Subscription**
	n=525	n=525	n=1050
Circumstances affecting willingness to share			
Strength of storm	185 (35%)	158 (30%)	519 (49%)
Previously living in affected area	69 (13%)	71 (14%)	171 (16%)
Friends/family living in affected area	242 (46%)	240 (46%)	446 (42%)
Existing travel commitments	137 (26%)	141 (27%)	343 (33%)
Limitations on willingness to share:			
Time until landfall	78 (15%)	-	-
Length of time vehicle gone	250 (48%)	236 (45%)	-
Time of day vehicle gone	46 (9%)	76 (14%)	-
Days of week vehicle gone	78 (15%)	104 (20%)	-
Compensation	255 (49%)	261 (50%)	534 (51%)
Tracking of vehicle	189 (36%)	192 (37%)	-
Ability to travel with vehicle	93 (18%)	100 (19%)	-

Among the circumstances affecting willingness to share, the survey results showed that having friends or family living in the affected area was the most influential factor in whether people would be willing to share their vehicle in both the evacuation and disaster relief scenarios. Among those who stated that the strength of the storm was a deciding factor in whether they would share their vehicle or not, the willingness to share increased as storm strength increased, likely due to an increase in the perceived need of those affected by the storm. In the evacuation scenario, this willingness was nearly twice as high for the category 4/5 hurricane than the tropical storms and category 1 hurricane. In the disaster relief scenario, the disparity between willingness to share for storm strength followed the same trends, but only increased by around 50% for the stronger storms.

Table 3.6: Strength of Storm Limitations

	Evacuation	**Disaster Relief**	**Subscription**
	n=185	n=158	n=519
Tropical Storm	56 (30%)	50 (32%)	109 (21%)
Category 1	58 (31%)	61 (39%)	136 (26%)
Category 2	65 (35%)	59 (37%)	185 (36%)
Category 3	86 (46%)	72 (46%)	292 (56%)
Category 4	105 (57%)	74 (47%)	318 (61%)
Category 5	113 (61%)	72 (46%)	341 (66%)

Among the limitations on the public's willingness to share, compensation, and length of time the vehicle is gone were the most common limitations requested. Table 3.7 shows the distribution of times that people would be willing to share while Table 3.8 shows the number of consecutive days respondents would share vehicles or experience delays. Table 3.9 shows the frequency of requests for each category of compensation.

Table 3.7: Length of Time Limitations

	Evacuation (n=250)	Disaster Relief (n=236)
<1 hour	6 (2%)	4 (2%)
1-4 hours	48 (19%)	64 (27%)
5-8 hours	66 (26%)	60 (25%)
9-12 hours	37 (15%)	18 (8%)
13-24 hours	9 (4%)	12 (5%)
Entire day	84 (34%)	78 (33%)

Table 3.8: Consecutive Days Limitations

	Evacuation	Disaster Relief	Subscription
	n=250	n=236	n=779
1 Day	31 (12%)	27 (11%)	129 (17%)
2 Days	82 (33%)	89 (38%)	229 (29%)
3 Days	67 (27%)	57(24%)	200 (26%)
4+ Days	70 (28%)	63 (26%)	221 (28%)
Note: Subject to time length limitations			

Table 3.9: Compensation Limitations

	Evacuation (n=255)	Disaster Relief (n=261)
Tax incentive	110 (43%)	102 (39%)
Insurance	200 (78%)	191 (73%)
Transportation	118 (46%)	112 (43%)
Cash compensation	172 (67%)	152 (58%)
Fuel/energy costs	165 (65%)	136 (52%)
IRS mileage rate	105 (41%)	99 (38%)

As shown in Table 3.7, even among respondents with a preference on when their vehicle could be shared, the largest percentage of them, at 34% and 33% for evacuation and disaster relief, respectively, would be willing to find transportation alternatives for an entire day to help with a disaster. When asked further about how many consecutive days respondents would be willing to share their vehicle, more than half of the respondents indicated a willingness to share for multiple days in both the evacuation and disaster relief scenarios as shown in Table 3.8.

Nearly half of the respondents in both scenarios expected some form of compensation for using their vehicle. Most common, as shown in Table 3.9, is the insurance of the vehicle while being used. This is understandable as it seems likely that governing organizations using private vehicles would be held responsible if damage occurred while sharing. However, some of the other requests such as cash compensation, although requested by a large number of people, would likely be infeasible for governing organizations.

Among the other limitations above, willingness to share decreases as hurricane landfall nears as shown in Table 3.10. For those worried about the time of day the vehicle is gone, respondents were slightly more willing to share overnight, shown in Table 3.11. There were no clear trends in willingness to share on a weekday versus a weekend, shown in Table 3.12. All in all, citizens, in general, showed a willingness to share their vehicle with 37% and 39% of people, for evacuation and disaster relief respectively, falling in the Willing/Extremely willing to share category. However, there certainly is a limit on the number of people that would consider this an acceptable idea, with 24% and 22% of people unwilling or extremely unwilling to share. When asked about concerns with sharing, the biggest concern was vehicle damage with 76% and 74% of people being concerned about damage for evacuation and disaster relief, respectively.

Table 3.10: Evacuation Landfall Sharing Limitations

Days Before Landfall	%	Count (n=78)
4 days before landfall	47%	37
3 days before landfall	45%	35
2 days before landfall	36%	28
1 day before landfall	18%	14
Any time before landfall	19%	15

Table 3.11: Time of Day Limitations

	Evacuation	Disaster Relief	Subscription
	n=46	n=76	n=794
12:00AM-4:00AM	14 (30%)	17 (22%)	281 (35%)
4:00AM-8:00AM	13 (28%)	21 (28%)	207 (26%)
8:00AM-12:00PM	14 (30%)	32 (42%)	202 (25%)
12:00PM-4:00PM	8 (17%)	19 (25%)	158 (20%)
4:00PM-8:00PM	5(11%)	15 (20%)	150 (19%)
8:00PM-12:00AM	8 (17%)	13 (17%)	211 (27%)
All of the above	15 (33%)	20 (26%)	221 (28%)

Table 3.12: Day of Week Limitations

	Evacuation	Disaster Relief	Subscription
	n=78	n=104	n=771
Weekday	21 (27%)	25 (24%)	175 (23%)
Weekend	12 (15%)	29 (28%)	231 (30%)
Both	45 (58%)	50 (48%)	331 (47%)

3.3 Subscription Adoption and Overview

In addition to the creation of the models of willingness to share, the survey aimed to understand the state of AV adoption in different scenarios. To do this, the survey asked numerous questions about AV adoption in general as well as AV adoption via subscription service. Table 3.13 outlines the responses to the general AV adoption questions as expected in the year 2025. As shown here, respondents were most comfortable with AV deliveries with almost 50% expecting some comfort with that scenario and only 8% expecting to never be comfortable with that. Thirty-four percent (34%) of people were at least somewhat comfortable riding in an AV while 25% of people expect to be at least somewhat comfortable in buying an AV. Purchasing an AV to share with family/friends or for income was quite unpopular with 25% and 37% of people saying they never expect to be comfortable with this. Finally, purchasing an AV to replace a respondent's regular vehicle had 32% of people saying they would never be comfortable with it. This shows that AV implementation could face a number of challenges in regard to societal acceptance in the coming years.

The perception of alternative AV implementation scenarios was mixed as well. Based on the results of the focus groups and survey pre-test, the SC general public seemed most accepting of a subscription rideshare alternative rather than the Purchase and Share or Micro-transit futures described previously. Based on the survey responses shown in Figure 3.1, 18% of respondents would be willing to consider purchasing AV subscriptions based on their current lifestyle. Respondents were most interested in the convenience and maintenance-free aspects of this future and most concerned about emergencies and no constant vehicle access.

When asked about a disaster scenario while having subscription AV ride-hailing as a primary source of transportation, respondents were asked what additional delay they would be willing to face to assist others in evacuation and transportation of disaster relief supplies. The results are shown in Table 3.14.

Table 3.13: Expected AV Adoption Comfort in 2025

	Very Comfortable	Somewhat Comfortable	Neutral	Somewhat Uncomfortable	Very Uncomfortable	Never
Riding in an AV	123 (12%)	232 (22%)	170 (16%)	210 (20%)	149 (14%)	166 (16%)
Delivery using AVs	207 (20%)	309 (29%)	259 (25%)	123 (12%)	72 (7%)	80 (8%)
Purchasing an AV	111 (11%)	145 (14%)	244 (23%)	165 (16%)	167 (16%)	218 (21%)
Purchasing an AV to share with friends/family	89 (8%)	146 (14%)	223 (21%)	168 (16%)	166 (16%)	258 (25%)
Purchasing an AV to share for income	37 (4%)	71 (7%)	141 (13%)	178 (17%)	235 (22%)	388 (37%)
Purchasing an AV for replacement of regular vehicle	54 (5%)	90 (9%)	142 (14%)	194 (18%)	232 (22%)	338 (32%)

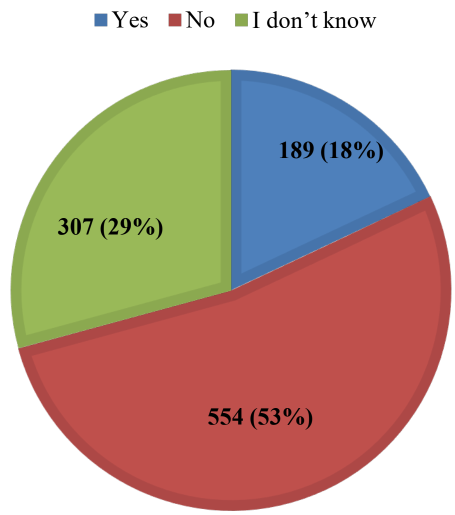

Figure 3.1: Willingness to Purchase AV Subscription Service

Table 3.14: Subscription Delay Willingness

Variable	Number	Percentage
No delay	216	21%
<5 minutes	50	5%
6-10 minutes	113	11%
11-15 minutes	178	17%
16-30 minutes	220	21%
31-60 minutes	150	14%
60+ minutes	123	12%

Although a large percentage of people would be opposed to experiencing any delay, most people seem accepting of delays to help others in this scenario. When asked about circumstances affecting willingness to share, storm strength and friends/family in the area were the most common responses, as shown in Table 3.5. Similar to the private ownership scenarios, respondents were about 3 times as willing to experience delays for a category 5 hurricane than a tropical storm, as shown in Table 3.6. Also, more than half of the respondents expected compensation in the form of future discounts for the added delay experienced to help others, shown in Table 3.5. As these subscription ride-hailing services are likely to be large corporations, these discounts could be feasible. Finally, respondents showed no clear difference in willingness to share between evacuation and disaster relief scenarios during the subscription future presented.

CHAPTER 4
Methodology

4.1 Ordinal Logistic (OL) Modelling

This study analyzed the survey data by creating ordered logit (OL) models. The dependent variables included five Likert-type answer choices describing a respondent's willingness to share a future autonomous vehicle for a) evacuation and b) disaster relief. Ordered probability models, such as the logit, have been used in the transportation field for years for dependent variables with three or more ordered categories (Washington, Karlaftis, & Mannering, 2011, p.345). These models have been used for the analysis of various types of survey data such as congestion charges (Zheng et al., 2014) and travel-related health risk perception (Hotle, Murray-Tuite, & Singh, 2020). Data with an ordered opinion as the dependent variable can often use the ordered logit model (Washington, Karlaftis, & Mannering, 2011, p.345).

Ordered logistic models with a number of explanatory variables can be written as in equation (4.1).

$$ln(\pi_j) = \alpha_j - (\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n) \quad (4.1)$$

where $x_1, x_2, \ldots, x_n$ are the explanatory variables, π_j = prob(score ≤ j) / prob(score > j), α_j is the intercept of the logit j, and β is the regression coefficient of each explanatory variable (Chen et. al., 2016). Each ordered category j has a separate intercept (α_j), but the same coefficients (β) for each explanatory variable (x).

The ordinal regression model in SPSS called the Polytomous Universal Model or PLUM is an extension of the general linear model to ordinal data using a logit link function (Norusis, 2005). The parameters in the ordered logistic model are determined using maximum likelihood estimation (Greene & Hensher, 2009). The log-likelihood function is described as in equation (4.2):

$$lnL = \sum_{i=1}^{n} \sum_{j=0}^{J} m_{ij} ln[F(\mu_j - \beta' x_i) - F(\mu_{j-1} - \beta' x_i)] \quad (4.2)$$

Here, $m_{ij} = 1$ if $y_i = j$ and 0 otherwise, where y_i is the value of a random variable. Maximization is performed following the constraints $\mu_{-1} = -\infty$, $\mu_0 = 0$ and $\mu_J = +\infty$. Also, β' and μ_j are unknowns and x_i are the constant values associated with the model parameters (Greene & Hensher, 2009; Greene, 2016).

Once the final model is produced, the output in SPSS provides parameter estimates for each ordered category threshold (α_j) and the coefficient of each explanatory variable ($\boldsymbol{\beta}=\{\beta_1, \beta_2, \ldots, \beta_n\}$),). To determine the likelihood of a given individual selecting an ordered category based on their response to each explanatory variable ($\boldsymbol{x}=\{x_1, x_2, \ldots, x_n\}$), one puts those responses into the right-hand side of Equation (4.3) (UCLA Statistical Consulting Group) and obtains the probability of selecting that category or a lower order category. At that point, one must subtract the sum of all previous categorical probabilities to find the probability of that individual selecting ordered category j. To determine which category is most likely to be selected, all ordered category thresholds should be checked for a given individual and the category with the highest probability is the most likely response.

$$P(j) = \frac{1}{1+e^{-\alpha_j + \beta_1 * x_1 + \cdots + \beta_n * x_n}} \quad (4.3)$$

The ordered logistic model assumes a) the dependent variable is ordinal, b) at least one independent variable is continuous, ordinal, or categorical, c) there is no multicollinearity, and d) the data meets the proportional odds assumption (Chen et al., 2016). The first two assumptions are met during variable selection.

The multicollinearity assumption was checked by ensuring no variables that are highly correlated are in the same model. This was checked throughout the modeling process by ensuring that all Spearman correlations between all variables were less than 0.4 for each model. The proportional odds assumption was checked through the parallel line test. The parallel line test provides the null hypothesis that the slope coefficients are the same across all categories. If the model fails that test, one can assume that all coefficients are not equal and the ordinal logit model is not an acceptable model (Williams, 2006; UCLA Statistical Consulting Group), and a generalized ordered logit model would be more appropriate.

4.2 Model Search

The ordinal logistic model building process began by inputting all potential independent variables into the model individually, noting each significance. After ordering variables by significance, the variables were then placed in the model one by one to determine if they improved the model (Heinze, Wallisch, & Dunkler, 2018) in a forward stepwise approach. The determination of whether the model was improved was an increase in the McFadden Pseudo R-Square value as well as 95% confidence that the parameter estimate was different from zero. This process was repeated until reaching the significance level of 0.25 from the list of individual variables shown partially in Table 4.1, as recommended for large sample sizes (Bendel & Afifi, 1977). Throughout the modeling process, the correlation between variables was checked and variables correlated above the 0.4 level were not included in the same model. The correlation matrix can be viewed in Table 3.4.

Table 4.1: P-Values of Selected Variables with Dependent Variables

	Evacuation Sharing				DR Sharing			
Variable	Estimate	Std Err	P Value	n	Estimate	Std Err	P Value	n
Demographics								
Gender – Women	.038	.158	.809	518	.054	.160	.738	511
High income (>$100,000 per year)	-.120	.175	.494	518	-.098	.178	.582	511
Household size	.010	.066	.875	512	.190	.070	.007**	506
Educated with a 4 year degree or more	.008	.158	.960	518	.311	.161	.053*	511
Highest education of vocational/technical school	.358	.429	.404	518	-.587	.431	.173	511
Age 65 or older	-.754	.213	.000***	518	-.206	.205	.315	511
Income under $15,000 per year	-.504	.296	.088*	518	-.056	.274	.837	511
Unemployed	.646	.320	.044**	518	-.016	.378	.965	511
Takes religious trips during a typical week	.458	.170	.007**	518	-.120	.172	.488	511
Living in Pee Dee region of South Carolina	.191	.198	.335	518	.508	.215	.018**	511
Living in urban area	.202	.255	.427	518	-.094	.226	.678	511
Technology								
Use of ride-hailing services 8+ times in past year	.671	.219	.002**	518	.162	.221	.463	511
0 or 1 social media accounts	-.886	.195	.000***	518	-.270	.185	.143	511
High comfort in AV deliveries in 5 years	.993	.163	.000***	518	.987	.116	.000***	511
High comfort in sharing AV for income in 5 years	1.144	.280	.000***	518	.958	.289	.001**	511
High number of technology features on newest vehicle	-.279	.220	.205	501	.498	.271	.066*	487
Evacuation Experience								
Household evacuation experience	.105	.170	.535	518	-.063	.169	.709	511
Experience evacuating with friends/family	1.925	.498	.000***	167	.834	.411	.042**	174
Received evacuation assistance from friends/family	1.346	.321	.000***	167	.571	.298	.055*	174
Giving and Volunteering								
Giving to charitable causes more than once per year	.382	.165	.021**	518	.446	.163	.006**	511
Volunteering more than once per year	.527	.160	.001**	518	.582	.162	.000***	511
Experience giving any disaster relief assistance	1.070	.168	.000***	518	.642	.168	.000***	511
Experience giving to assist friends/family in disaster relief efforts	.514	.184	.005**	518	.832	.196	.000***	511
Commuting								
Commuting by single-occupancy vehicle	-.281	.267	.294	335	-.949	.271	.000***	319
Commute Length	-.005	.007	.499	324	.011	.008	.181	315
Regular weekly commute schedule	-.126	.213	.553	335	-.066	.228	.772	319
Note: *** p<.001, ** p<.05, * p<.1								

4.3 Model Application for AV Availability

The estimation of autonomous vehicle availability was divided into two parts. The first part was the ordered logit model described in section 4.1. The second part of the estimation is applying the estimated model to the population level. Because the statistical model developed from the survey used individual-level data, the population-level data should also be in the same format.

The Census data provides the sum of people/households at specified geographical areas for a specific variable. The aggregate level data is not applicable for the model application in the context of this research, so a synthetic population was generated using a population sample seed and Census count data as a control.

The population synthesis process needs two types of input, one is the disaggregate population sample and the other one is the marginal control distribution (PopulationSim Introduction, 2020). First, the population sample seed was obtained from the 2018 Public Use Microdata Sample (PUMS) for the state of South Carolina. For each household or individual, the PUMS data contains detailed information including socio-demographic variables, e.g., sex, education level, income, and employment status (U.S. Census Bureau, 2019.). Compared to the Census data aggregated counts, the PUMS data focuses on individual/individual household level responses. To protect the confidentiality of respondents, ACS limited the area codes of PUMS data at the Public Use Microdata Area level; this geographic level contains more than 100,000 people in each area. The second step was to obtain the marginal control; the total number of people from each sub-county was obtained from the ACS 2018 data. The controls were set at the sub-county level because that was the desired spatial resolution for this project. The population synthesis process was executed in the PopulationSim package (0.4.2 version) in the Python Environment. The resulting synthetic population contained two files: one was for each household in the entire state of South Carolina and the other file was for individuals that corresponded to each household. Demographic variables contained in these files were: age and employment status for person file; income for the household file. These variables were the variables included in the final ordinal logit model (see Chapter 5). These two files were combined so that each household is associated with only one decision-maker, this process was done by randomly select one person's record in each household. Other significant variables in the model were generated using the observed distribution from the survey (see Table 3.3).

The data preparation terminated after all required variables had been generated. Based on Equation 4.1, the probability of each outcome was calculated using Equation 4.4:

$$prob(score = j) = \pi_j - \pi_{j-1} \tag{4.4}$$

From the probability of score 5 (combined extremely willing and willing from the survey) of all households generated, the percentage of willingness to share (s) of the public in each sub-county was determined. This was achieved by using equation 4.5 for each of the sub-counties.

$$\text{s} = \frac{\text{sum of the probability of score 5 of all households generated}}{\text{total number of households generated}} \tag{4.5}$$

The percentage of willingness to share (s) was then converted into the number of available AVs using equation 4.6.

4.4 Monte Carlo simulation model

From the survey responses, approximately 32% of South Carolina citizens were willing to share their (future) AVs to assist with hurricane evacuation. Based on this public willingness to share their AVs and the percentage of AVs used by the general public (i.e., AV market penetration), a Monte Carlo simulation model was developed to determine that how many CTNH can be evacuated using only shared AVs. The reason for using a simulation model instead of a simple analytic model was to allow for uncertainty in processes and to allow the model to grow in complexity. Any operational characteristic or constraint can be added to the model at a later time. As a starting point, the following assumptions were made.

1. AVs were only available in the non-evacuation region.
2. One household had only one AV.
3. One AV evacuated one CTNH in a single trip.
4. All AVs available in a sub-county started and ended their trips at the centroid of that sub-county.
5. All CTNH in an evacuation zone were picked up at the centroid of that evacuation zone.
6. Shelters had unlimited capacity.

Figure 4.1 illustrates the processes implemented in the simulation model. The pseudocodes showed in Figure 4.2 shows how the logic was implemented in Python. In step 1, the model read a number of input files as described below.

1. *A GIS map of South Carolina*. In this project, as shown in Figure 4.3, South Carolina was divided into two regions: the evacuation region and the non-evacuation region. The evacuation region is shown in red in Figure 4.3 (gallowayra_SCDOT, 2018). The evacuation region consists of multiple evacuation zones; the South Carolina Emergency Management Division designated these areas as “SC Hurricane Regional Evacuation Zones.” The non-evacuation region is shown in blue in Figure 4.3 (United States Census Bureau 2020c). In this study, the spatial scale used to represent the non-evacuation region is at the census county division level, referred to as “sub-counties” hereafter.
2. *The centroids of the evacuation zones in the evacuation region*. ArcMap was used to locate the centroids of SC Hurricane Regional Evacuation Zones (gallowayra_SCDOT, 2018). The coordinates of these centroids were then exported from ArcMap as a text file. To read these coordinates in Python, a built-in package, *json* was used.
3. *The centroids of the sub-counties in the non-evacuation region*. ArcMap was used to locate the centroids of South Carolina sub-counties (United States Census Bureau 2020c). The coordinates of these centroids were then exported from ArcMap as a text file. In order to read these coordinates in Python, a built-in package, *json* was used.
4. *Shelter locations*. Shelter locations were selected based on the details provided in the “State of South Carolina CTN evacuation operations plan” report (South Carolina Emergency Management Division, 2019). The coordinates of the shelter locations were exported from ArcMap as a text file and the *json* package was used to read these coordinates in Python.
5. *Spatial network*. Input data 2, 3, and 4 were combined and all these points together represented the spatial network. This network was considered as an undirected graph G = (V, E). The set V consisted of vertices representing locations of centroids and shelter locations from input data 2, 3, and 4. The set E consisted of edges connecting any two vertices in V.
6. *Percentage of willingness to share AVs*. Section 4.3 explained how the public’s willingness to share their AVs was obtained from the survey data. These percentages were provided for each sub-county.
7. *Percentage of AV market penetration*. The AV market penetration was obtained from the literature (Bansal and Kockelman 2017). It was assumed that the percentage of market penetration was the same for all sub-counties in South Carolina.
8. *The average number of persons per household in each of the counties in South Carolina* (United States Census Bureau 2020b).
9. *The population in each of the evacuation zones* (gallowayra_SCDOT 2018).
10. *The population in each of the sub-counites in the non-evacuation region* (United States Census Bureau 2020a).
11. *The number of households in each of the sub-counites in the non-evacuation region* (United States Census Bureau 2020a, United States Census Bureau 2020b).

12. *Percentage of CTN population that need to be evacuated* (South Carolina Emergency Management Division 2019).
13. *Probability distribution of time for which an AV would be available* (survey data from this study).
14. *The average speeds of AVs during evacuation* (South Carolina Department of Transportation 2020). Only two speeds were used, one for daytime and one for nighttime.

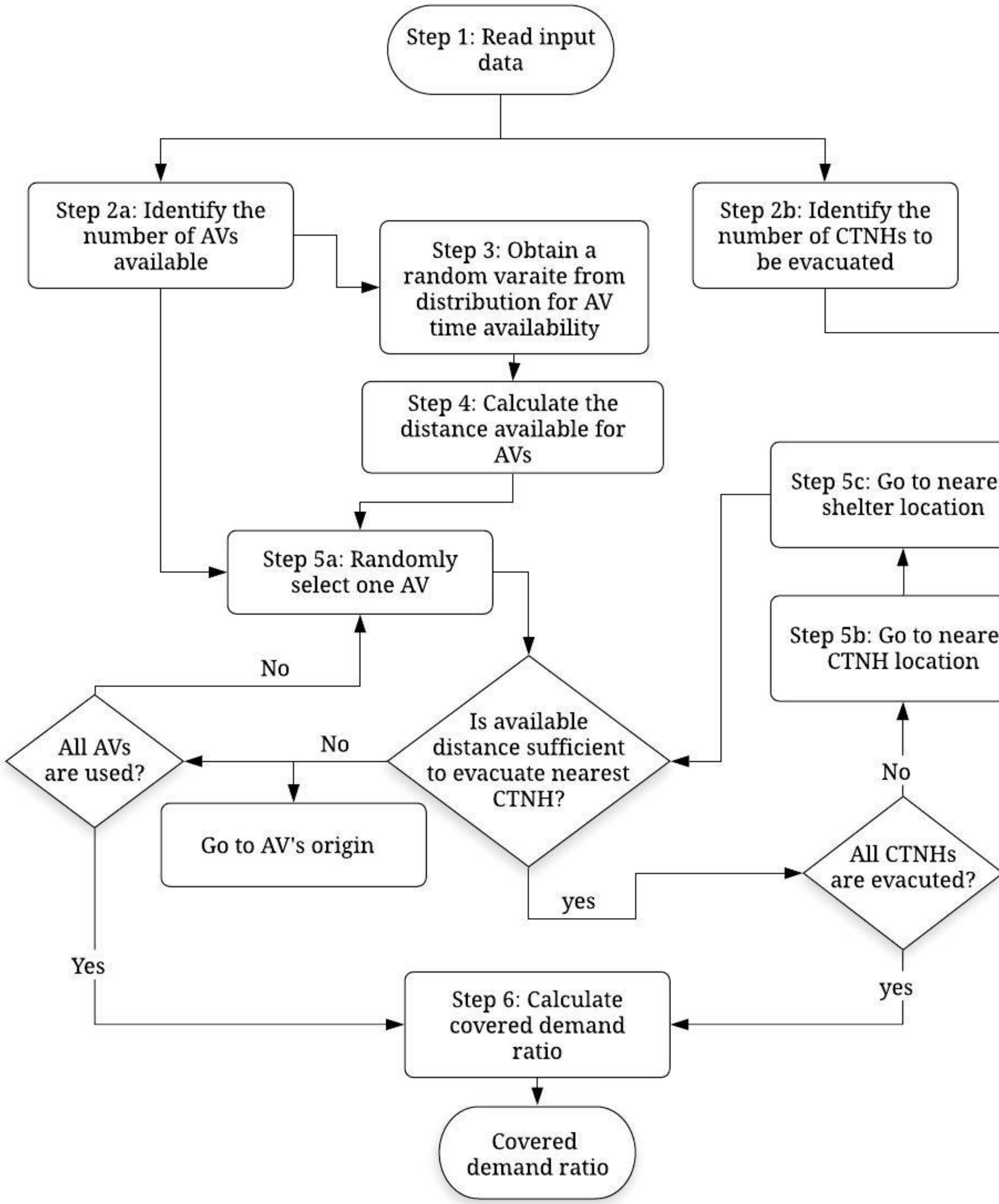

Figure 4.1: Logic of Monte Carlo Simulation Model

In step 2a, the total number of AVs available in the non-evacuation region was determined. The model first calculated the number of AVs available in each sub-county using equation (4.6). The product, $p \cdot h$, in equation (4.6) gave the total number of AVs owned by the public in a sub-county. Multiplying this value by the percentage of willingness to share gave the total AVs available for evacuation in that sub-county. The total number of AVs available in the entire non-evacuation region of South Carolina was obtained by adding the number of AVs available for all sub-counties in the non-evacuation region.

$$n = s \cdot p \cdot h \tag{4.6}$$

Where
n = number of AVs available in a sub-county,
s = percentage of willingness to share the AVs for emergency evacuation,
p = percentage of AV market penetration, and
h = number of households in a sub-county.

In step 2b, the total number of CTNH in the evacuation region was determined. The model first calculated the number of CTNH in each evacuation zone using equation (4.7). For each evacuation zone in the evacuation region, the quotient $\frac{pp}{hs}$ in equation (4.7) gave the total number of households. Multiplying this value by the percentage of CTN population gave the number of CTNH in the evacuation zone. The total number of CTNH in the evacuation region was obtained by adding the number of CTNH from all evacuation zones in the evacuation region of South Carolina.

$$np = \left(\frac{pp}{hs}\right) pc \tag{4.7}$$

where,
np = number of CTNH in an evacuation zone,
pp = total population in an evacuation zone,
hs = average persons per household of the county in the evacuation zone, and
pc = percentage of CTN population in South Carolina.

```
Require
Set of AVs available = L
Set of CTNH in the evacuation region requiring assistance in evacuation = P
Set of evacuation shelters = K
Discrete distribution of time for which an AV is available
Maximum number of iteration
Distance between any two nodes in the network
Initialize
Iteration number, Itr = 0
A list to store the covered demand ratio = C

While Itr ≤ maximum number of iteration
    Randomly generate time for which an AV is available from the discrete distribution for all AVs in the list L
    Calculate the maximum distance (in miles) for which an AV is available for all AVs in the list L
    Maximum distance available for an AV i ∈ L = dmax_i
    Initialize
    Vehicle routes of all AVs, all_routes = [ ]
    Number of CTNH evacuated, CTNH_evc = [ ]

    While |L| >0 and |P| >0
        randomly select one AV from L, namely i
        distance covered by the AV i, dcov = 0
        remaining distance available for the AV i, drem = dmax_i
        vehicle route of the AV i, route_i = [ ]
        add the location of i to route_i
        a location preceded to the CTNH location, j = i
        While drem > 0
        a = Select the CTNH from the list P that is closest to location j
        b = Select a shelter from the list K that is closest to the location of a
        dcov = dcov + d(j, a) + d(a, b)
        drem = dmax_i – dcov
        If drem – d(b, i) ≥ 0
            remove a from P and add the location of a and b to route_i (b followed by a)
            add a to CTNH_evc
            j = b
            else
        remove i from L and add the location of i to route_i
        drem = 0
        end If
        add route_i to all_routes
        end While
    covered demand ratio = |CTNH_evc| / |P|
    end While
    Itr =Itr +1
    add covered demand ratio to the list C
end While
```

Figure 4.2: Pseudocode for the Monte Carlo Simulation Model

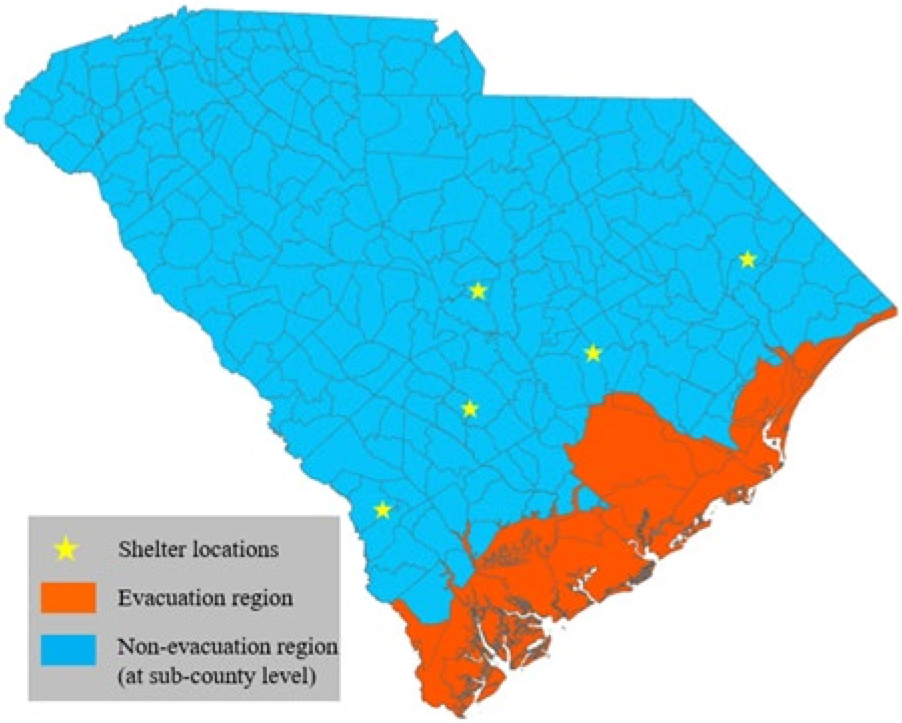

Figure 4.3: South Carolina Evacuation Region Map layers (*Source: United States Census Bureau 2020c, gallowayra_SCDOT, 2018*)

In step 3, the time (i.e., duration) for which each AV is available was determined. From the survey responses, different respondents indicated different durations for which they were willing to share their AVs. Using the numbers selected for each duration category, a discrete distribution was constructed as shown in Table 4.2. The time for which an AV is available was drawn from this discrete distribution with probabilities equal to the percentages indicated in Table 4.2. The midpoints of the selected range were used as the available duration.

In step 4, the maximum distance (in miles) for which each AV is available was calculated using equation (4.8) from the time availability and average evacuation speed. The evacuation speed of AVs was obtained from the Traffic Polling and Analysis System on the SCDOT website (South Carolina Department of Transportation 2020).

$$d = t \cdot v \tag{4.8}$$

where,
d = distance for which an AV is available,
t = time for which an AV is available,
v = average speed of an AV (estimated by considering the delay during an emergency)

In step 5, the model determined the total number of CTNH evacuated using the available AVs. In step 5a, the model randomly selected an AV from the pool of available AVs. Then, the model started the evacuation process using the selected AV. First, the model checked to see if the distance available was sufficient for the AV to go to the nearest CTNH location, drop off the CTNH at the nearest shelter, and go back to its original location. If the available distance was sufficient, the model checked whether all CTNH had been evacuated. If not, the model simulated the AV evacuating the CTNH: going to the nearest CTNH (step 5b) and dropping the CTNH off at the nearest shelter (step 5c). When the AV reached the shelter location, the model checked to see if the AV's remaining available distance was sufficient to evacuate another nearest CTNH. If not, the AV returned to its original location. Otherwise, the model again checked for whether all CTNH had been evacuated. If all CTNH had been evacuated, then the model calculated the covered demand ratio (CDR) using equation 4.9. Otherwise, the AV was assigned to evacuate another nearest CTNH. This process was repeated until either no more AVs were available or all CTNH had been evacuated.

$$\text{CDR}=\frac{\text{Number of CTNH evacuated}}{\text{Total number of CTNH}} \tag{4.9}$$

Table 4.2: Discrete Distribution of AV Time Availability

#	Time range	Percentage	Count	Midpoint
1	Less than 1 hour	2.40%	6	0.5 hours
2	1-4 hours	19.20%	48	2.5 hours
3	5-8 hours	26.40%	66	6.5 hours
4	9-12 hours	14.80%	37	10.5 hours
5	13-24 hours	3.60%	9	18.5 hours
6	Entire day	33.60%	84	12 hours
	Total	100%	250	

CHAPTER 5
Results

5.1 Modeling Background

Following the methodology described previously, the research team ended with three final ordinal logit models. Non-significant hypothesis variables were added to these models to double-check for statistical significance, leading to a total of six models. The decision was made to present two models relating to the evacuation scenario for a number of reasons. First, there was a drastic difference in sample size and McFadden Pseudo R-Square between the two models. Secondly, the small sample model did not contain any demographic variables, making it unreliable to apply to a population. The models are detailed in Table 5.1.

5.1.1 Full Sample Evacuation (Preferred FS Evacuation Model)

The preferred full sample (FS) evacuation model had 518 observations. In logit modeling, the McFadden Pseudo R-square is often used to test how well a model fits. However, in ordinal regression, this value typically has low values. Furthermore, it should not be interpreted as the R-Square value is for linear regression as it is calculated differently. Previous researchers using this type of modeling have reported adjusted McFadden Pseudo R-square values anywhere between 0.012 and 0.138 (Hotle et al., 2020). For this model specifically, the adjusted McFadden Pseudo R-Square value was 0.067. Details are shown in Table 5.1.

This model contained eight significant variables. Age 65 or older, income under $15,000 per year, and 1 or fewer social media accounts had a negative coefficient while being unemployed, taking regular religious trips, high comfort in AV deliveries, high comfort in sharing an AV for income, and any experience giving for disaster relief had positive coefficients. In ordinal regression, these coefficients have been adapted to be interpreted intuitively, with negative coefficients signifying a lower willingness to share (Norusis, 2005).

5.1.2 Small Sample Evacuation Model (Preferred SS Evacuation Model)

The preferred small sample (SS) evacuation model had 167 observations. Notably, the adjusted McFadden Pseudo-R Square value for this model was 0.111, which was significantly higher than the full-sample evacuation model. However, this model contained significantly fewer observations than the FS Evacuation model. Details are shown in Table 5.1.

This model contained five significant variables. Ride-hailing eight or more times in the past year, high comfort in AV deliveries, experience evacuating with friends or family, receiving evacuation assistance from friends or family, and experience giving to disaster relief causes were all positively significant in this model. The major difference between this model and the other evacuation model was the inclusion of evacuation experience variables. All of the respondents used in this model had some form of evacuation experience. Therefore, it was significantly less representative of the population as a whole but helped to show characteristics of those who had experienced hurricanes. This model also had a better fit, based on the McFadden value, than the other models produced.

Table 5.1: Ordinal Logit Regression Models

Variable	Preferred SS Evacuation Model	SS Model with Hypotheses	Preferred FS Evacuation Model	FS Model with Hypotheses	Preferred DR Model	DR Model with Hypotheses
	Estimate (Std. Error)	Estimate (Std. Error)	Estimate (Std. Error)	Estimate (Std. Error)	Estimate (Std. Error)	Estimate (Std. Error)
Demographics						
H1: Gender - Women		-.081 (.447)		.012 (.228)		.508** (.234)
H4: High income (>$100,000 per year)		.368 (.601)		-.038 (.279)		-.352 (.286)
H8: Household size		-.230 (.180)		-.133 (.091)	.194** (.090)	.270** (.100)
H5: Educated with a 4 year degree or more		-.696 (.475)		-.190 (.246)		.169 (.247)
Highest education of vocational/technical school					-1.483** (.582)	-1.724** (.625)
H2: Age 65 or older		.120 (.919)	-.531** (.228)	-.059 (.466)		1.147** (.567)
Income under $15,000 per year			-.728** (.333)	-.802 (.548)		
Unemployed			1.219** (.357)	.671 (.565)		
H11: Takes religious trips during a typical week		.616 (.450)	.374** (.178)	.616** (.246)		-.034 (.249)
Living in Pee Dee region of South Carolina					.725** (.304)	.857** (.330)
H12: Living in urban area		.118 (.890)		.448 (.375)		.105 (.339)
Technology						
H9b: Use of ride-hailing services 8+ times in past year	.734** (.363)	.652 (.468)		.206 (.297)		-.099 (.306)
H9c: 0 or 1 social media accounts		-.481 (.662)	-.540** (.213)	-.706** (.302)		.176 (.308)
High comfort in AV deliveries in 5 years	.603** (.304)	.522 (.445)	.747*** (.172)	.811*** (.233)	.746** (.223)	.925*** (.237)
High comfort in sharing AV for income in 5 years			.604** (.296)	.770** (.374)	.758** (.367)	.806** (.390)
H9a: High number of technology features on newest vehicle		-.745 (.650)		-.538* (.326)		.548 (.430)
Evacuation Experience						
H3: Household evacuation experience		(A)		-.248 (.242)		-0.424* (0.24)
Experience evacuating with friends/family	1.756** (.527)	.991 (.743)				
Received evacuation assistance from friends/family	.693** (.347)	1.301** (.531)				
Giving and Volunteering						
H10a: Giving to charitable causes more than once per year		-.187 (.574)		-.128 (.262)	..498** (.219)	.520** (.259)
H10b: Volunteering more than once per year		.422 (.511)		.105 (.245)		-.147 (.255)
Experience giving any disaster relief assistance	1.449*** (.353)	1.941** (.531)	.886*** (.180)	1.077*** (.253)		
Experience giving to assist friends/family in disaster relief efforts					.729** (.250)	.789** (.270)
Commuting						
Commuting by single-occupancy vehicle					-0.799** (.298)	-.802** (.334)
H6: Commute length		-.008 (.016)		.000 (.008)		.007 (.009)
H7: Regular weekly commute schedule		.424 (.444)		-.199 (.246)		.286 (.263)
Number of responses	**167**	**101**	**518**	**313**	**315**	**302**
McFadden Pseudo R-Square	**0.121**	**0.181**	**0.072**	**0.091**	**0.072**	**0.094**
Adjusted McFadden Pseudo R-Square	**.111**	**.118**	**.067**	**.069**	**.063**	**.069**
Parallel Line Test	**(.247) Pass**	**(1.0) Pass**	**(.549) Pass**	**Pass (.380)**	**(.817) Pass**	**Pass (.053)**

Note: *** p<.001, ** p<.05, * p<.1

(A) : Not included because redundant with evacuating with friends/family and receiving evacuation assistance from friends/family

Synthetic Population Generation

Overall, 1,894,711 households were included in the population data with their demographics synthesized. These demographics variables were recoded into binary variables for model application. Other significant variables in the preferred FS Evacuation model were generated at the population level from the observed percentages. The preferred FS Evacuation model was then applied to the population level data. The predicted probability of picking score 5 for sub-counties across the state of South Carolina had a mean of 32% with a standard deviation of 0.6%.

5.1.3 Disaster Relief Model (Preferred DR Model)

The final model had 315 observations. For this model, the adjusted McFadden Pseudo R-Square was 0.063. Details are shown in Table 5.1. This model contained eight significant variables. Household size, residing in the Pee Dee region of South Carolina, high comfort in AV deliveries, high comfort in AV sharing for income, giving to charitable causes more than once per year, and experience giving to friends and family for disaster relief were found to be positively associated with willingness to share. The highest educational attainment of technical/vocational school and commuting by single-occupancy vehicle were found to be negatively associated with willingness to share. Notably, the sample size here was smaller as the model only included respondents that commuted to work or school in a typical week.

5.1.4 Monte Carlo simulation model

Experimental design

The Monte Carlo simulation model was used to determine the percentage of CTNH that could be evacuated (measured by CDR) at the predicted level of willingness of the South Carolina citizens to share their AVs. For all experiments, the model used the public willingness to share the AVs obtained from section 4.3 for each of the sub-counties (average value over all sub-counties was 32%). For market penetration, the experiments used projections estimated by Bansal and Kockelman (2017). They projected the AV market penetration for future years under 8 scenarios. These scenarios were derived based on three factors affecting the AV purchase by the public: the projected annual increase in the people's willingness to pay (WTP) for the new technologies, annual drops in technology price, and changes in government regulations on AV deployment. The AV market penetration projected under scenarios 1, 3, 6, and 8 for years 2025, 2030, 2035, and 2040 (Bansal and Kockelman, 2017) were selected to perform the Monte Carlo simulation as the values in the other scenarios were close to one of the selected scenarios. Scenario 1 was with constant WTP, a 10% drop in the technology price, and no regulations. Scenario 3 was with constant but no-zero WTP, 10% drop in the technology price, and no regulations; in this scenario, the tenth percentile WTP (among non-zero WTP individuals) for the individual's household demographic cohort was used. Scenario 6 was with a 5% annual increase in WTP, a 10% drop in the technology price, and with regulations. And scenario 8 was with a 10% annual increase in WTP, a 10% drop in the technology price, and with regulations. The CDR was determined for 16 different combinations of years (2025, 2030, 2035, and 2040) and scenarios (1, 3, 6, and 8); 15 simulation runs were performed for each of the 16 combinations. The market penetration values used are shown in Table 5.3. For each of the future years considered, scenario 8 gave a higher percentage of AV market penetration (AV market penetration = 1 for 2030 and beyond) than that of scenario 3 which represented the most conservative estimate of AV market penetration. The percentage of CTN was assumed to be 5% for each of the evacuation zones (South Carolina Emergency Management Division 2019).

To simulate the AV evacuating the CTNHs (that is starting from its origin, going to the CTNH location, and dropping them off to the shelters), the model needed a spatial network. The spatial network considered in this project consisted of three elements: the AV's origin, the CTNH location, and the shelter location. Since it was assumed that all AVs in a sub-county start and end their trips at the centroid of the sub-counties, the number of AVs' origin points was equal to the number of sub-counties in the non-evacuation region (i.e., 265 points from where the AVs start and end their trips). It was also assumed that all CTNH in an evacuation zone were picked up at the centroid of the evacuation zone; hence, the total number of pickup points in the evacuation region was equal to the number of evacuation zones in the evacuation region (i.e., 20 pickup points). Five shelter locations were selected based on the details provided in the "State of

South Carolina CTN evacuation operations plan" report (South Carolina Emergency Management Division, 2019). As per this report, the neighboring counties of the evacuation zones could be ideal locations for shelters. The selected shelter locations were in Richland, Clarendon, Marion, Orangeburg, and Allendale counties. Hence, the network consisted of 290 nodes. The model calculated the Euclidean distance between any two nodes in the network to simulate the process of evacuation.

It was assumed that 70% of the evacuees evacuated during the day and 30% evacuated during the night (Wong et al. 2018). The evacuation speed of AVs was obtained from the Traffic Polling and Analysis System on the SCDOT website (South Carolina Department of Transportation 2020). The traffic speeds along the South Carolina highways during the past 6 hurricanes were collected and the average speed for the day and night times were obtained separately. The average evacuation speed during the day was 20 mi/hr, and the average evacuation speed during the night was 40 mi/hr. Other parameters used by the model are summarized in Table 5.2.

Table 5.2: Other parameters used by the Monte Carlo simulation model

#	Parameter
1	The average number of persons per household in each of the counties in South Carolina (United States Census Bureau 2020b).
2	The population in each of the evacuation zones (gallowayra_SCDOT 2018).
3	The population in each of the sub-counites in the non-evacuation region (United States Census Bureau 2020a).
4	The number of households in each of the sub-counites in the non-evacuation region (United States Census Bureau 2020a, United States Census Bureau 2020b)
5	Probability distribution of time for which an AV would be available (survey data from this study).
6	Number of AVs available (equation 4.6)
7	Number of CTNH requiring assistance in evacuation (equation 4.7)
8	Distance available for each AVs (equation 4.8)

Results

Given four different market penetration scenarios and four future years, there were a total of 16 different combinations. Table 5.3 shows the average CDR obtained from 15 Monte Carlo simulation runs for each of the 16 combinations. At the projected AV market penetration levels, 29% (scenario 3) to 87.5% (scenario 8) of the CTNH could be evacuated in 2025, 54% (scenario 3) to 100% (scenario 8) of the CTNH could be evacuated in 2030, 75.2% (scenario 3) to 100% (scenario 8) of the CTNH could be evacuated in 2035, and 88.8% (scenario 3) to 100% (scenario 8) of the CTNH could be evacuated in 2040. It is clear now in 2020 that level 4 AVs will not be ready for deployment by 2025. Manufacturers have encountered unexpected issues with the development and testing of level 4 AVs. Specifically, concerns about safety have delayed progressive regulation to allow their testing on public roads.

The relationship between CDR and AV market penetration (p) is shown in Figure 5.1. It can be observed that for $p \leq 20\%$, the CDR increases linearly with respect to p. For $p > 20\%$, the relationship between CDR and p resembles a concave function. For scenarios 1, 3, and 8, it can be observed that the CDR is approximately 0.9 at 20% AV market penetration. This result suggests that with a 20% AV market penetration, approximately 90% of the CTNH could be evacuated. For scenario 6, the result indicates that approximately 85% of the CTNH could be evacuated with a 20% AV market penetration. Scenario 3 was the most conservative scenario. It predicted that a 100% CDR could not be achieved until sometime after 2040. For scenario 8, 100% CDR could be achieved by the year 2030, scenario 6 by the year 2035, and scenario 1 by the year 2040. For all four scenarios, with a 20% AV market penetration, more than 80% of CTNH could be evacuated. This finding is aligned with the Pareto Principle (Juran et.al., 2005); 80% of outcomes come from 20% of the sources.

Table 5.3: Covered Demand Ratio for Different Scenarios

Year	Scenario 1*		Scenario 3*		Scenario 6*		Scenario 8*	
	Market penetration	Covered Demand ratio	Market penetration	Covered Demand ratio	Market penetration	Covered Demand ratio	Market penetration	Covered Demand ratio
2025	11.10%	57.50%	5.20%	29.00%	15.10%	69.40%	19.40%	87.50%
2030	19.70%	89.10%	10.30%	54.00%	27.20%	99.90%	33.80%	100.00%
2035	28.60%	99.90%	15.00%	75.20%	38.30%	100.00%	44.20%	100.00%
2040	37.00%	100.00%	19.20%	88.80%	45.70%	100.00%	74.70%	100.00%

*scenarios from the work of Bansal and Kockelman (2017).

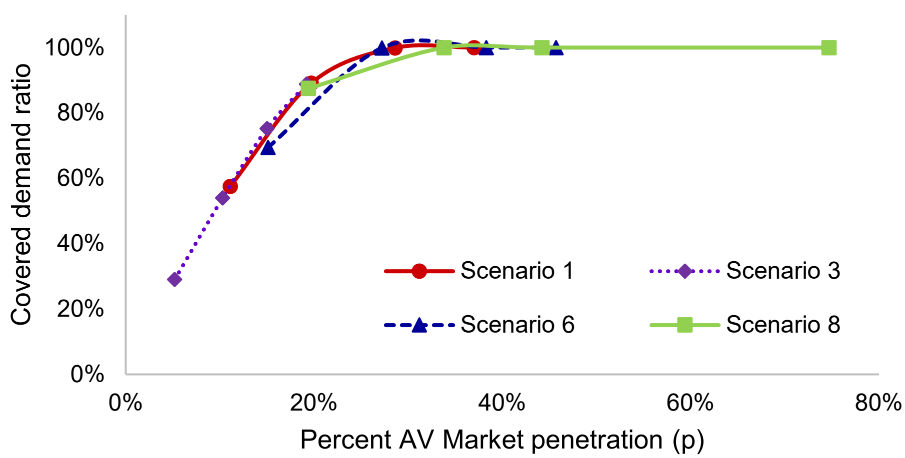

Figure 5.1: Effect of AV Market Penetration on CDR

In Figure 5.2, four alternative models are presented: polynomial, logistic, exponential, and hyperbolic tangent. These models could be used to determine the minimum required market penetration level needed to cover a certain evacuation demand. Based on the root mean squared errors (RMSE), the logistic and polynomial regression models performed equally well and were superior to the exponential and hyperbolic tangent models. The polynomial model was the simplest among the four models; however, it can only be used when $p \leq 28\%$. The logistic regression model has a much more complex form; however, it could be used for any $0 \leq p \leq 100\%$. The logistic regression model can be used to derive important insight. Specifically, for each additional 1% increase in AV market penetration, there was a 5.5% increase in CDR.

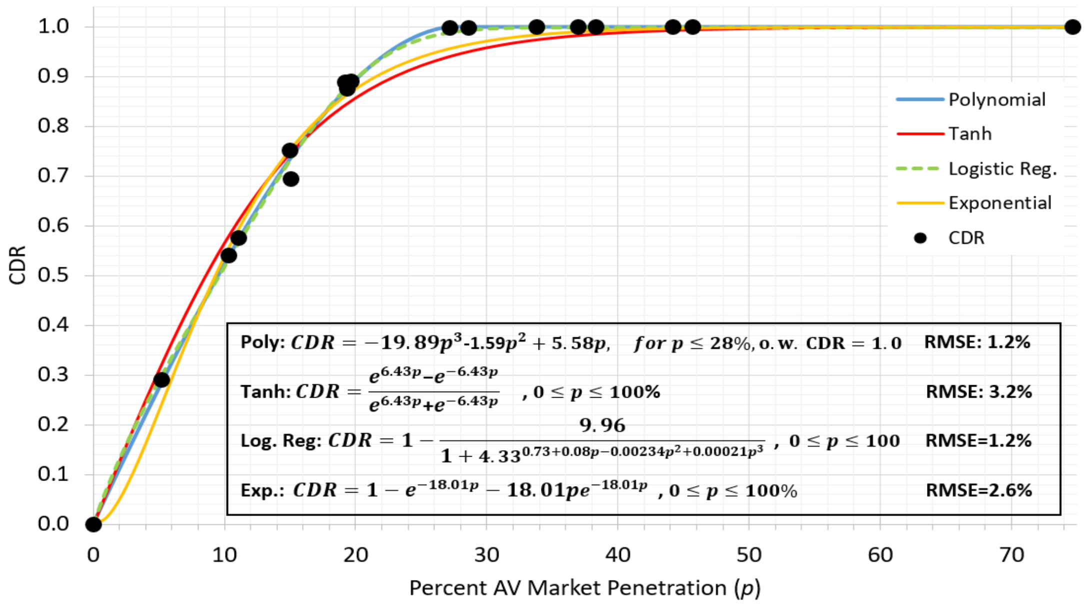

Figure 5.2: AV Market Penetration-CDR Models

5.2 Hypotheses Revisited

This discussion was based on the results of the multi-variable logit models including each hypothesis variable shown in Table 5.1, as well as the single-variable models testing the individual relationship between each variable and the dependent variables shown in Table 4.1. The final results of the hypotheses are shown succinctly in Table 5.2. Notably, there were a number of hypotheses with different outcomes for the evacuation and disaster relief scenarios. To test potential reasons for this, the research team compared the evacuation and disaster relief samples to determine whether these differences were due to each sample's demographics or notable differences in willingness to share. These results are explained further in Chapter 3 and shown in Appendix A and Appendix B.

H1: Women are positively associated with willingness to share their vehicles for evacuation and disaster relief.

This hypothesis was rejected for evacuation but partially supported for disaster relief. Although women showed no significant differences from men in both evacuation models in Table 5.1, women were significantly ($p<.05$) more willing to share in the disaster relief multi-variable model. However, gender was a non-significant ($p>.1$) factor in the single-variable models testing the variable's relationship with willingness to share for evacuation and disaster relief contexts, as shown in Table 4.1. After comparing the evacuation and disaster relief samples using the Chi-Square Test, no significant differences were found in the female to male proportion of each sample, shown in Appendix A. Using the Mann-Whitney Test, there was also no difference in the female willingness to share for evacuation and disaster relief shown in Appendix B.

Although women are expected to be more generous than men (Eckel & Grossman, 2003), perhaps their slower adoption of new technology (Piao et al., 2016; Hohenberger, Spörrle, & Welpe, 2016; Hulse et al., 2018) or the different daily travel responsibilities, such as transporting children (MacDonald, 1999), counteracted any greater willingness to share for evacuation. Alternatively, women could be more empathetic to the struggling households in an area following a storm than those in fear before a storm, as women have been known to be generous in response to disasters (Bergdoll et al., 2019, Eckel, Grossman, & Milano, 2017).

H2: Older respondents (Age 65 and older) are negatively associated with willingness to share their vehicle for disaster assistance.

This hypothesis was supported for evacuation and rejected for disaster relief. Respondents aged 65 or older were negatively associated ($p<.05$) with a willingness to share in the preferred full sample evacuation model. Similarly, this age group was highly significant ($p<.001$) and negative in the single-variable model testing its relationship with willingness to share for evacuation, shown in Table 4.1. There was a positive relationship ($p<.05$) between age 65+ and willingness to share for disaster relief in the multi-variable model shown in Table 5.1. Notably, when comparing the two evacuation and disaster relief samples using the Mann-Whitney U Test, the over 65 age group was found to be significantly more willing to share in the disaster relief sample than the evacuation sample. Potentially, this shows that the over 65 age group prefers sharing for disaster relief over evacuation, a topic that would require more study to confirm. Here, the literature was mixed as older people show little interest in the adoption of new technology (Czaja et al., 2006), but are more generous than young people (Eckel & Grossman, 2003). It is possible that the sample in the hypothesis models, which included only the population that traveled to work, removed some of the over 65 population and accounted for some of the differences in results for that demographic. For example, the strong negative relationship between the over 65 and evacuation sharing variables, shown in Table 4.1, did not appear in the evacuation model with hypotheses. However, it did not account for the differences in the single variable model differences between evacuation and disaster relief sharing.

H3: Households with evacuation experience are positively associated with willingness to share their vehicles for disaster assistance.

This hypothesis was rejected for both evacuation and disaster relief. Evacuation experience was not a significant factor for modeling willingness to share except for being weakly negative ($p<.1$) in the disaster relief model. This was unexpected as previous literature pointed to previous evacuation experiences having a significantly positive effect on giving to disaster causes (Eckel, Grossman, & Milano, 2007).

However, receiving evacuation assistance from friends or family was found to be positively associated with willingness to share in the small sample evacuation model ($p<.05$). A positive association was determined in the single-variable models (Table 4.1) between this individual variable and willingness to share in both the evacuation ($p<.001$) and disaster relief contexts ($p<.1$). Similarly, experience evacuating with friends and family was positively associated with willingness to share in the preferred small sample evacuation model ($p<.05$) in Table 5.1. Likewise, in the single-variable models shown in Table 4.1, experience evacuating with friends and family was a significant, positive factor for sharing in both the evacuation ($p<.001$) and the disaster relief ($p<.05$) contexts. Our study showed that evacuation experience, in general, had little effect on willingness to share, but experience receiving assistance in an evacuation, specifically from family and friends, had a significant impact.

H4: Respondents with a higher income (over $100,000 per year) are positively associated with willingness to share their vehicle for disaster assistance.

This hypothesis was rejected for both the evacuation and disaster relief scenarios. There was no significant relationship found between high income and willingness to share from these survey results. Notably, other definitions of high income (over $150,000 and over $200,000) were tested in the models, yet none of these variables were significant. Previous literature found that, although the wealthy were often more generous (Brown, Harris, & Taylor, 2012), they typically commuted more (Besser et al., 2008), which could explain the limited willingness to share their vehicles. However, income was found to have some effect on willingness to share. Respondents with an income less than $15,000 per year were found to be less willing to share in the preferred full-sample evacuation model ($p<.05$) in Table 5.1. This was supported by the single-variable model in Table 4.1 indicating a somewhat negative association ($p<.1$). This relationship made some sense as AVs are expected to be expensive (Litman, 2019) and it is understandable that people with poverty-level incomes would highly value something of that cost. Within South Carolina, approximately 13% of households have income under $15,000 per year (US Census Bureau, 2020).

H5: Households with higher education levels (Bachelor's degree or higher) are positively associated with willingness to share their vehicle for disaster assistance.

This hypothesis was rejected for both evacuation and disaster relief. There was no significant association between high education level and willingness to share in the multivariable models. However, in the single-variable model, there was a positive, somewhat significant relationship ($p<.1$) between high education and willingness to share in the disaster relief context, as shown in Table 4.1. Similar to income, people with higher education typically drive more than those with less education (Kim, Anorve, & Tefft, 2019), which may cancel out the greater generosity found in previous studies (Brown, Harris, & Taylor, 2012) as well as the greater adoption of new technologies (Czaja et al., 2006). Regarding the income/education relationship, the high income and high education variables were not correlated above the 0.4 threshold, as shown in Table 3.4. However, when comparing the ordered education variable and the semi-continuous income variable, they were correlated to a greater extent (0.465).

Interestingly, having vocational/technical school as a respondent's highest level of education was found to be negatively significant for the disaster relief model ($p<.05$). This could possibly be explained by the fact that people attending technical schools typically work skilled, blue-collar jobs such as construction, health care, manufacturing, and transportation (Luchansky, 2015). Most of these jobs inherently do not allow the ability to telecommute, which could lead to an increased dependence on a personal vehicle.

H6: Households with longer commutes are negatively associated with willingness to share a vehicle for disaster assistance.

This hypothesis was rejected for both evacuation and disaster relief. No significant association was found between commute length and willingness to share. However, a couple of variables related to commuting and employment were found to be significant in some models.

First, unemployed respondents were found to be positively associated with sharing ($p<.05$) in the preferred full-sample evacuation model in Table 5.1. This was also shown in the single-variable model testing willingness to share for evacuation, shown in Table 4.1. This was likely because respondents who are unemployed do not have the schedule associated with employment, and therefore, would not be as negatively affected by being without a vehicle for some period of time.

Also, respondents who commute by single-occupancy vehicle were negatively associated ($p<.05$) with sharing in the disaster relief model. This variable was also extremely negatively significant ($p<.001$) in its single-variable model for willingness to share in the disaster relief context, shown in Table 4.1. This relationship was understandable as a person who typically drives alone to work every day depends on their car and may live in a place where transit and carpooling are not options.

H7: Households with a regular commuting schedule are positively associated with willingness to share their vehicle for disaster assistance.

This hypothesis was rejected for both evacuation and disaster relief. No significant association was found between respondents with a regular commute schedule and willingness to share. Based on our sample, approximately 70% of employed respondents had a regular commuting schedule, but there was no significant effect of this schedule.

H8: The number of people in a household is negatively associated with a willingness to share a vehicle for disaster assistance.

This hypothesis was rejected for both evacuation and disaster relief. Countering this hypothesis, household size was found to be positively significant in the disaster relief model. This was also visible in the single-variable model testing the variable's relationship with sharing in the disaster relief context shown in Table 4.1. Interestingly, based on the Mann-Whitney sample comparisons conducted, large households (5+) were significantly more willing to share in the disaster relief scenario than the evacuation scenario, shown in Appendix B.

The literature was mostly inconclusive on this topic, which explains why household size had no significant association with evacuation sharing. However, larger households are known to travel more (Kim, Anorve, & Tefft, 2019) and commute further (Crane, 2007), which would suggest less willingness to share a vehicle. On the other hand, households with dependent children are more generous than those without (Schokkaert, 2006) so perhaps that was the stronger relationship in the disaster relief sample. Furthermore, larger households typically own a greater number of vehicles than smaller households, potentially indicating a surplus of vehicles (BTS, 2017).

When specifically checking the sample in this study, household size and number of vehicles were somewhat correlated with a value of 0.317. When replacing the household size variable with the calculated variable, vehicles per person within a household, the new variable was somewhat positively significant ($p<.1$) in the full-sample evacuation model ($p=.051$) and somewhat negatively significant in the disaster relief model ($p=.07$), providing little clarity on that relationship.

H9: Respondents' trust and adoption of technology will be significantly associated with willingness to share a vehicle for disaster assistance.

Although not included in the hypothesis, respondents more comfortable with AV technology showed a significantly higher willingness to share in nearly all models and variable relationships. Respondents indicating a high comfort in using AVs for deliveries in five years were positively associated with willingness to share in the full sample evacuation model ($p<.001$), disaster relief model ($p<.001$), and the small sample evacuation model ($p<.05$). Similarly, this variable was extremely positively significant ($p<.001$) in the single-variable models testing willingness to share in both the evacuation and disaster relief contexts.

Likewise, high comfort in sharing AVs for income in five years was significant ($p<.05$) in both the full sample evacuation model and the disaster relief model. Also, this variable was individually extremely significant ($p<.001$) in the evacuation context and significant ($p<.05$) in the disaster relief context, as shown in the single-variable models in Table 4.1. As a precaution prior to inclusion in any models, this variable's relationship was tested with a high willingness to share a vehicle for evacuation and returned with a Pearson correlation coefficient of 0.172, which indicates a relationship, but not strong enough of one to be a concern.

H9a) Respondents owning a vehicle with a high number of recent innovations will be positively associated with willingness to share a vehicle for disaster assistance.

This hypothesis was rejected for both evacuation and disaster relief. Nevertheless, a somewhat significant positive relationship ($p<.1$) was found between owning a high-tech vehicle and willingness to share for disaster relief in the single-variable model, shown in Table 4.1. However, in the full-sample evacuation model, this variable was somewhat negatively ($p<.1$) associated with willingness to share. However, these cases were not strong enough to prove a relationship between vehicle innovations and sharing. When comparing the evacuation and disaster relief samples, researchers determined the samples to be very different for this variable, both in the number of responses per scenario and average response for each scenario, shown in Appendix A and Appendix B, with the evacuation sample having significantly more respondents with a high-tech vehicle, but lower willingness to share. In all, although these respondents were comfortable adopting newer technologies specifically in vehicles, they may also highly value them, potentially reducing any impact of willingness to share.

H9b) Respondents with a high number (8 or more) of ride-hailing service uses in the past year will be positively associated with willingness to share vehicles for disaster assistance.

This hypothesis was supported for evacuation but rejected for disaster relief. A high number of ride-hailing service uses in the past suggested a significantly increased willingness to share AVs for evacuation, based on the preferred small-sample model ($p<.05$) in Table 5.1. Furthermore, this positive relationship ($p<.05$) was also shown in the single-variable model, as shown in Table 4.1. As both of the dependent variables in this study discuss willingness to share, it is interesting that this relationship is rejected for disaster relief, but supported in the evacuation context.

H9c) Respondents with a low number of social media accounts (0-1) will be negatively associated with willingness to share their vehicle for disaster assistance.

This hypothesis was supported for evacuation but rejected for disaster relief. Respondents with few (0-1) social media accounts were less willing to share vehicles for evacuation, based on the full-sample evacuation model ($p<.05$) in Table 5.1. A similar direction of effect ($p<.001$) was shown in the single-variable model shown in Table 4.1. When comparing the evacuation and disaster relief samples, it was discovered that respondents with little social media presence were significantly less willing to share for evacuation than disaster relief, shown using the Mann-Whitney test in Appendix B. Social media has been one of the biggest social changes in the past decade, with a significant majority of people across the country participating today (Pew Research Center, 2019). Those who have hesitated in adopting social media may be somewhat fearful of new technology, and therefore, may be less willing to adopt AVs and consider sharing them.

H10: Households that H10a) give more than once per year will be positively associated with a willingness to share a vehicle for disaster assistance.

This hypothesis was partially supported for evacuation and fully supported for disaster relief. The single-variable models indicated giving more often had a significantly positive ($p<.05$) effect on willingness to share in both evacuation and disaster relief contexts, as shown in Table 4.1. However, in the multi-variable models in Table 5.1, respondents who gave more than once per year were only found to be significantly more willing to share in the disaster relief model ($p<.05$). Interestingly, the evacuation sample had a somewhat significantly ($p<.1$) larger proportion of participants giving more than once per year, perhaps accounting for some of the differences in the results, shown via Chi-Square Tests in Appendix A. The literature was consistent in showing that those who give more, in general, give more to help with disasters (Eckel, Grossman, & Milano, 2007; Brown, Harris, & Taylor, 2012; Bergdoll et al., 2019).

Interestingly, survey respondents who had experience giving to disaster relief causes in any form were more willing to share. This variable was extremely significant ($p<.001$) in both the small sample and full sample evacuation models. It also had an extremely significant ($p<.001$) individual effect in both the evacuation and disaster relief single-variable models, as shown in Table 4.1. When specifying giving this assistance to friends and family, the variable was also significant ($p<.05$) in the multi-variable disaster relief model in Table 5.1. Further, respondents with experience providing disaster relief assistance to friends and family showed a significantly positive relationship with willingness to share for evacuation ($p<.05$) and an extremely significant ($p<.001$) relationship with the willingness to share for disaster relief in the single-variable contexts, as shown in Table 4.1.

Households that H10b) volunteer more than once per year will be positively associated with a willingness to share a vehicle for disaster assistance.

This hypothesis was partially supported for both evacuation and disaster relief. Again, in the single-variable models, volunteering more often was significant for both evacuation ($p<.05$) and disaster relief ($p<.001$), as shown in Table 4.1. However, this variable was not significant in any of the final multivariable models.

H11: Regular religious activity is positively associated with willingness to share a vehicle for disaster assistance.

This hypothesis was supported for evacuation but rejected for disaster relief. Respondents with regular religious activity were significantly ($p<.05$) more willing to share vehicles in the preferred full-sample evacuation model shown in Table 5.1. Similarly, this variable had a significant and positive association ($p<.05$) with a willingness to share for evacuation, as shown in the single-variable context in Table 4.1. However, it had no significant association with sharing for disaster relief, as shown in Table 4.1, or any use in the disaster relief model shown in Table 5.1. Previous literature showed religious activity and willingness to give were strongly associated (Brown, Harris, & Taylor, 2012; Eckel & Grossman, 2003), but it is unclear why this relationship only appeared in the evacuation model.

H12: Residing in urban areas is positively associated with a willingness to share a vehicle for disaster assistance.

This hypothesis was rejected for both evacuation and disaster relief as it was not significant in any multi-variable models or single-variable comparisons with the dependent variables. Although this variable had no significant effect on willingness to share, it was notable that the disaster relief sample had significantly more urban respondents than the evacuation sample, shown via the Chi-Square Test in Appendix A. The literature on this topic pointed strongly to an increased willingness to share for respondents residing in an urban area. Urbanites have been found to have shorter commutes (Crane, 2007), be more active in the sharing economy (Smith, 2016), and have shown more interest in adopting AV technology (Bansal et al, 2016; Liljamo et al., 2018). In the survey, this question was selected by respondents with no context so perhaps some respondents were not knowledgeable about the definitions of community types.

Although not directly related to community type, respondents in South Carolina's Pee Dee region were found to be positively associated with sharing ($p<.05$) in the disaster relief model. This association was also in the single variable model for willingness to share for disaster relief, as shown in Table 4.1. A description of this variable is provided in Appendix C. The Pee Dee region does not contain a city in the top five most populated cities in South Carolina (US Census Bureau, 2020), indicating it is more rural. This region, home to Myrtle Beach, has been affected year after year by hurricanes, and therefore, understands some of the things associated with evacuation and the need for disaster assistance. Therefore, when specified that the storm is not affecting them, it is understandable that they would be willing to help.

Table 5.4: Results of Hypotheses

Variable	Hypothesized Result	Evacuation	Disaster Relief
Gender - Female	+	Rejected	Partially supported
Age 65 or older	-	Supported	Rejected*
Evacuation experience	+	Rejected	Rejected
High income (>$100,000/year)	+	Rejected	Rejected
Highly educated (Bachelors or higher)	+	Rejected	Rejected
Longer commutes	-	Rejected	Rejected
Regular commutes	+	Rejected	Rejected
Larger household	-	Rejected	Rejected*
Ownership of highly advanced vehicle	+	Rejected	Rejected
High use of ride-hailing	+	Supported	Rejected
Few (0-1) social media accounts]	-	Supported	Rejected
Gives more than once per year	+	Partially supported	Supported
Volunteers more than once per year	+	Partially supported	Partially supported
Regularly attends religious services	+	Supported	Rejected
Resides in an urban setting	+	Rejected	Rejected

* Significantly positive relationship determined in the model

CHAPTER 6
Conclusions

6.1 Summary and Relevance

This project examined shared uses of autonomous vehicles (AVs) in evacuation and disaster relief. The research team examined existing literature and held three focus groups to understand the South Carolina public's feelings on vehicle technology, the sharing economy, disaster experiences, and AV implementation scenarios. Based on the literature and focus groups, a survey was drafted that addressed public concerns on the many potential topics affecting decisions to share an AV for hurricane evacuation or disaster relief. Using that survey, numerous ordered logistic models were built to identify characteristics of the population willing to share vehicles. In addition, concerns and limitations to this willingness to share were aggregated. As mentioned in the introduction, the objective of this project was to aid emergency management officials in considering disaster assistance options for a world with autonomous vehicles.

Although autonomous vehicle implementation has been extensively researched, there have not been many studies looking into the use of AVs for disaster assistance. Even in regard to applying the sharing economy to disaster assistance, very little has been studied. This project has the potential to provide emergency management officials with new alternatives for evacuating vulnerable populations and delivering relief supplies to those in need.

6.2 Conclusions and Limitations

Based on the results of this survey, the general public in South Carolina seems open to the idea of using AV's to assist in disaster scenarios in the future, with 37% and 39% of citizens willing or extremely willing to share for evacuation and disaster relief, respectively (based on the survey responses). The general public is also open to the idea of subscription-based autonomous ride-hailing as an addition to the standard private ownership future. Ordered logistic regression was used in this study to determine significant characteristics of the willing and unwilling population. The notable variables and their relationship with sharing for evacuation and disaster relief are discussed below.

6.2.1 Demographics

A number of demographic variables were tested throughout the modeling process to determine notable characteristics associated with increased or decreased willingness to share vehicles for evacuation and disaster relief. In the evacuation context, being unemployed and taking regular trips for religious purposes were found to have a positive effect on sharing. For disaster relief, women, age 65+, Pee Dee region, and large household respondents were positively associated with willingness to share.

Being over age 65 and having a household income below $15,000 were found to have a negative effect on sharing for evacuation. For disaster relief, vocational school as the highest education was found to be negatively associated with sharing AVs.

6.2.2 Technology

Variables testing technology adoption and comfort were also tested for significant associations with the willingness to share. Here, greater use of ride-hailing services (8 or more times in a year) and high comfort in using AVs for deliveries and sharing AVs for income in five years were positively associated with sharing in evacuation contexts. For disaster relief, high comfort in using AVs for deliveries and sharing AVs for income in five years were also positively associated with sharing. In contrast, respondents with few (0-1) social media accounts were negatively associated with sharing in the evacuation context.

6.2.3 Evacuation Experience

Researchers also expected evacuation experience to have an impact on willingness to share vehicles for disaster scenarios. The models determined that experience evacuating with friends or family and receiving evacuation assistance from friends or family both had a positive effect on sharing for evacuation. Similarly, experience evacuating with friends or family had a somewhat positive effect on sharing for disaster relief, but this was not confirmed in the final multi-variable model.

6.2.4 Giving and Volunteering

Giving and volunteering were also expected to be meaningful in their effects on vehicle sharing. Here, experience giving to disaster relief was positively associated with sharing for evacuation. Similarly, respondents who give more frequently than annually as well as those who have experience giving to friends/family in response to a disaster were more willing to share for disaster relief. Also, giving more frequently than annually and volunteering more frequently than annually had a somewhat positive effect on sharing vehicles in the evacuation context. Finally, volunteering more than annually had a somewhat positive effect on sharing in the disaster relief context.

6.2.5 Commuting

Commuting was also expected to have an effect on sharing vehicles for disaster assistance. Here, the models showed that commuting by a single-occupancy vehicle had a negative effect on sharing vehicles for disaster relief.

6.2.6 Evacuation using AVs

After applying survey results to the synthetic South Carolina population, it was determined from the synthetic population generated that approximately 32% of South Carolina citizens were willing to share their AVs to assist with mass evacuation due to the potential impact of a major hurricane. A Monte Carlo simulation model was developed to test the potential of using only shared AVs to evacuate the CTNH for different scenarios of AV market penetration. The most optimistic scenario (scenario 8) predicted that a CDR of 100% could be achieved in the not too distant future once AVs start gaining market share. It was observed that for $p \le 20\%$, the CDR increased linearly with respect to p, and for $p > 20\%$, the relationship between CDR and p resembled a concave function. The logistic regression model generated from the simulation results showed that when $p \le 20\%$, there was a 5.5% increase in the CDR for each additional 1% increase in AV market penetration. With a 20% AV market penetration, approximately 85% to 90% of the CTNH could be evacuated. Lastly, the experiment results indicated that an AV market penetration of 30% to 35% (depending on the scenario considered) was sufficient to evacuate all CTNH requiring evacuation assistance.

6.2.7 Study Limitations

It is important to note that the evacuation and disaster relief samples were not the same. For the most part, the samples were not significantly different. However, a couple of hypothesis variables, such as being over the age of 65, having zero or one social media accounts, having a high-tech vehicle, and having a large household were discovered to show significantly different degrees of willingness to share between the two samples.

Similarly, regarding the survey, results should be used very carefully as a basis for future study. As this is a stated preference survey regarding a novel topic, the research team recognizes that some part of the survey sample is likely to have some over-enthusiasm for the idea and possibly had difficulty fully following and comprehending the scenarios provided. In the same regard, a number of assumptions were made in the presentation of the disaster scenarios that could have been missed by survey respondents and, in turn, have an effect on their willingness to share. These assumptions are:

1. The household has the same number of vehicles as it does today.
2. The household has at least one AV.
3. The household has the same composition (dependents, employment, location, income) as it currently does.
4. The household will not be affected by the storm in any way.
5. The shared vehicles shared will not enter hazardous areas.

In the future, some of these assumptions could be removed or further explored. For example, households without any desire to own an AV could be removed from the disaster scenarios. Similarly, as AVs become more common, future surveys could provide different storm scenarios or ask questions in response to a specific disaster.

Although willingness to share shows that shared AVs could provide needed assistance to emergency management officials, a number of limitations must be considered. First, although willingness to share was high among respondents, comfort purchasing and riding in an AV was low. This suggests that an AV sharing system for evacuation and disaster relief, like the one presented, could be feasible in South Carolina, but likely not in the near future. By the time a large enough percentage of the population adopts AVs, views on AV sharing could be drastically different.

Similarly, part of this project was determining limitations on willingness to share AVs for a disaster. Potentially, an important limitation discovered was the desire to be compensated. Among the survey sample, about half of respondents expected to be compensated for sharing. Although some compensation options listed could potentially be feasible for states, such as vehicle insurance, others, such as cash compensation, could render an AV sharing system infeasible. Otherwise, the length of time a vehicle is gone was determined to be an important limitation on people's willingness to share as well as information on their vehicles' location. Respondents showed some major concerns with this disaster-based vehicle sharing system including the potential for damage and insurance if damage does occur.

This study was directed at South Carolina residents. Other states, regions, or nations are likely to have quite different results for a survey like this. Even within South Carolina, the sample population was slightly biased toward the higher income and more educated citizens, who are more likely to purchase AVs.

The simulation model developed to determine the percent of the critical transportation needs households relied on the estimated willingness to share from the ordered logit models. Three additional limitations of the simulation model included: 1) current populations and demographics were used to predict the CDR in future years; in future years these may or may not be the same, 2) the evacuation speeds were assumed to be 20 mi/hr during the day and 40 mi/hr during the night and 3) it was assumed that one AV can evacuate an entire household. These assumptions could be explored in future studies.

6.3 Future Directions

Based on the results of this study, autonomous vehicle sharing for evacuation and disaster relief assistance is a feasible idea but would require significantly more study and technological advancements before being implemented. Future research could apply the results of discrete choice modeling to a population to determine if AV sharing could reasonably cover a large-scale evacuation. This type of survey could also be distributed in a different geography to determine regional differences in survey responses and feasibility in other geographies. In addition, some of the common limitations determined in this survey could be further explored to determine if they could potentially be a barrier to the feasibility of this idea. For example, infeasible compensation desires could be categorized as unwilling to share or respondents only willing to share at unpopular evacuation times, such as overnight (Lindell et al., 2005), could be categorized as unwilling to share. Similarly, alternative AV futures such as subscription rideshare or micro-transit could be further explored to determine if the same type of system would be feasible if AVs are adopted in a different format. Finally, the use of different dependent variables, digging deeper into technology adoption and the sharing economy, for example, could allow for analysis using different models, which could provide more detailed results. All in all, this study has found the idea of AV sharing for evacuation and disaster relief has the potential to improve governmental response to natural disasters and improve the ability to minimize the loss of life associated with these disasters today.

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APPENDICES

Appendix A

Comparison of Sample for Evacuation and Disaster Relief Survey Scenarios

Table A.1: Sample Comparison for Selected Variables Using a Test of Proportions

Variable	Evac Number	Evac %	DR Number	DR %	Total %	Zstat	Decision
Unwilling to share	125	24%	114	22%	23%	0.692	Same
Somewhat unwilling to share	36	7%	30	6%	6%	0.706	Same
Neutral	50	10%	48	9%	10%	0.142	Same
Somewhat willing to share	116	22%	123	24%	23%	-0.637	Same
Willing to share	191	37%	196	38%	38%	-0.491	Same
Demographics							
Gender - Women	256	49%	267	52%	51%	-0.908	Same
Highest education of vocational/technical school	19	4%	18	4%	4%	0.125	Same
Age 65 or older	87	17%	95	19%	18%	-0.755	Same
Income under $15,000 per year	40	8%	48	9%	9%	-0.959	Same
Unemployed	37	7%	24	5%	6%	1.661	Same
Takes religious trips during a typical week	173	33%	162	32%	33%	0.580	Same
Living in urban area	57	11%	75	15%	13%	-1.762	Same
Technology							
Use of ride-hailing services 8+ times in past year	87	17%	80	16%	16%	0.496	Same
0 or 1 social media accounts	111	21%	127	25%	23%	-1.303	Same
High comfort in AV deliveries in 5 years	266	51%	239	47%	49%	1.469	Same
High comfort in sharing AV for income in 5 years	56	11%	51	10%	10%	0.436	Same
High number of technology features on newest vehicle	79	15%	53	10%	13%	2.340	Different
Evacuation Experience							
Household evacuation experience	167	32%	174	34%	33%	-0.617	Same
Experience evacuating with friends/family	24	14%	25	14%	14%	0.001	Same
Received evacuation assistance from friends/family	55	33%	56	32%	33%	0.148	Same
Giving and Volunteering							
Giving to charitable causes more than once per year	329	64%	298	58%	61%	1.708	Same
Volunteering more than once per year	263	51%	246	48%	49%	0.844	Same

Experience giving any disaster relief assistance	326	63%	327	64%	63%	-0.352	Same
Experience giving to assist friends/family in disaster relief efforts	134	26%	121	24%	25%	0.813	Same
Commuting							
Commuting by single-occupancy vehicle	279	83%	255	80%	82%	1.105	Same
Regular weekly commute schedule	229	68%	231	72%	70%	-1.135	Same
Income							
Low Income (<$35,000)	93	18%	124	24%	21%	-2.482	Different
Middle Income ($35,000-$99,999)	276	53%	245	48%	51%	1.712	Same
High Income (+$100,000)	149	29%	142	28%	28%	0.348	Same
Race							
Caucasian/White	357	69%	338	66%	68%	0.950	Same
Black/African American	133	26%	138	27%	26%	-0.484	Same
Other	30	6%	37	7%	7%	-0.942	Same
Education							
High School Education or less	83	16%	104	20%	18%	-1.801	Same
Bachelors or higher	263	51%	249	49%	50%	0.656	Same
Household Size							
1	63	12%	72	14%	13%	-0.916	Same
2	210	41%	201	39%	40%	0.395	Same
3	93	18%	107	21%	19%	-1.210	Same
4	89	17%	81	16%	17%	0.574	Same
5+	57	11%	45	9%	10%	1.179	Same
Age							
18-24	71	14%	69	14%	14%	0.095	Same
25-34	80	15%	80	16%	16%	-0.094	Same
35-44	92	18%	97	19%	18%	-0.506	Same
45-54	97	19%	89	17%	18%	0.546	Same
55-64	91	18%	81	16%	17%	0.738	Same
65-74	72	14%	75	15%	14%	-0.356	Same
75+	15	3%	20	4%	3%	-0.901	Same
Region							
Upstate	125	24%	144	28%	26%	-1.478	Same
Midlands	169	33%	150	29%	31%	1.134	Same
Lowcountry	119	23%	127	25%	24%	-0.707	Same

PeeDee	105	20%	90	18%	19%	1.088	Same
Commute Length							
<10 minutes	46	9%	57	11%	10%	-1.215	Same
10-14	55	11%	75	15%	13%	-1.960	Same
15-19	69	13%	46	9%	11%	2.198	Different
20-24	46	9%	37	7%	8%	0.966	Same

Table A.2: Sample Comparison for Selected Variables Using Chi Square Test

Variable	df	Pearson Chi Square	Significance
Willingness to Share	4	1.315	0.859
Demographics			
Gender - Women	1	0.824	0.364
High Income (+$100,000)	1	0.121	0.728
Household Size	4	3.53	0.473
Bachelors or higher	1	0.430	0.512
Highest education of vocational/technical school	1	0.016	0.900
Age 65 or older	1	0.570	0.450
Income under $15,000 per year	1	0.919	0.338
Unemployed	1	2.760	0.097**
Takes religious trips during a typical week	1	0.337	0.562
PeeDee	1	1.183	0.277
Living in urban area	1	3.104	0.078***
Technology			
Use of ride-hailing services 8+ times in past year	1	0.246	0.620
0 or 1 social media accounts	1	1.697	0.193
High comfort in AV deliveries in 5 years	1	2.159	0.142
High comfort in sharing AV for income in 5 years	1	0.190	0.663
High number of technology features on newest vehicle	1	5.092	0.024*
Evacuation Experience			
Household evacuation experience	1	0.381	0.537
Experience evacuating with friends/family	1	0.000	0.999
Received evacuation assistance from friends/family	1	0.022	0.883
Giving and Volunteering			
Giving to charitable causes more than once per year	1	2.918	0.088**
Volunteering more than once per year	1	0.713	0.399

Experience giving any disaster relief assistance	1	0.124	0.725
Experience giving to assist friends/family in disaster relief efforts	1	0.662	0.416
Commuting			
Commuting by single-occupancy vehicle	1	1.221	0.269
Regular weekly commute schedule	1	1.288	0.256
Commute Length	8	12.364	0.136
Other Demographics			
Income	9	7.932	0.54
Hispanic	1	1.503	0.220
Education	7	6.661	0.465
Age	6	1.814	0.936
Region	3	3.84	0.279
Commute Days per week	4	4.635	0.327
Number of Vehicles	4	2.827	0.587
Marital Status	4	2.394	0.664
Number of Dependents	5	5.328	0.377
Community Type	3	6.431	0.092****
Employment Status			
Employed Full-Time	1	0.168	0.682
Employed Part-Time	1	5.892	0.015*
Homemaker	1	0.818	0.366
Retired	1	0.336	0.562
Student	1	0.005	0.945
Unable to work	1	2.664	0.103
Race			
Caucasian/White	1	0.903	0.342
African American/Black	1	0.235	0.628
Other	1	0.888	0.346
* - More evacuation responses (p<.05), ** - More evacuation responses (p<.1) *** - More disaster relief responses (p<.1) **** - More suburban evacuation, more urban disaster relief responses (p<.1)			

Appendix B

Comparison of Responses for Evacuation and Disaster Relief Survey Scenarios using Mann-Whitney U Test

Table B.1: Sample Comparison for Selected Variables Using Mann-Whitney Test

Variable	Evacuation n	Evacuation Mean Rank	Disaster Relief n	Disaster Relief Mean Rank	Mann-Whitney U	Z	Significance	Decision
Willingness to Share	518	507.49	511	522.61	128458	-0.851	0.395	Same
Demographics								
Gender - Women	256	257.85	267	265.98	33114	-0.641	0.521	Same
Highest education of vocational/technical school	19	21.21	18	16.67	129	-1.328	0.184	Same
Age 65 or older	87	83.67	95	98.67	3451.5	-1.994	0.046	Different
Income under $15,000 per year	40	40.68	48	47.69	807	-1.327	0.185	Same
Takes religious trips during a typical week	173	175.22	162	160.29	12764.5	-1.474	0.14	Same
Technology								
Use of ride-hailing services 8+ times in past year	87	87.98	80	79.68	3134	-1.178	0.239	Same
0 or 1 social media accounts	111	108.48	127	129.13	5825	-2.4	0.016	Different
High comfort in AV deliveries in 5 years	266	247.87	239	258.71	30423	-0.895	0.371	Same
High comfort in sharing AV for income in 5 years	56	54.40	51	53.56	1405.5	-0.161	0.872	Same
High number of technology features on newest vehicle	79	60.61	53	75.27	1628.5	-2.264	0.024	Different
Evacuation Experience								
Household evacuation experience	167	171.46	174	170.56	14452	-0.088	0.93	Same
Experience evacuating with friends/family	24	27.98	25	22.14	228.5	-1.665	0.096	Same
Received evacuation assistance from friends/family	55	60.38	56	51.7	1299	-1.541	0.123	Same
Giving and Volunteering								
Giving to charitable causes more than once per year	329	307.82	298	320.82	46989	-0.941	0.347	Same
Volunteering more than once per year	263	249.63	246	260.75	30935.5	-0.899	0.369	Same
Experience giving any disaster relief assistance	326	330.40	327	323.61	52193	-0.486	0.627	Same
Experience giving to assist friends/family in disaster relief efforts	134	121.57	121	135.12	7245.5	-1.569	0.117	Same

Commuting								
Commuting by single-occupancy vehicle	279	267.28	255	267.74	35511.5	-0.036	0.972	Same
Regular weekly commute schedule	229	225.55	231	235.41	25315.5	-0.83	0.406	Same
Income								
Low Income (<$35,000)	93	106.69	124	110.73	5551.5	-0.49	0.624	Same
Middle Income ($35,000-$99,999)	276	257.99	245	264.39	32979	-0.505	0.614	Same
High Income (+$100,000)	149	143.61	142	148.5	10223.5	-0.516	0.606	Same
Race								
Caucasian/White	357	344.43	338	351.77	59057.5	-0.502	0.616	Same
Black/African American	133	135.43	138	136.55	9101.5	-0.122	0.903	Same
Other	30	31.1	37	36.35	468	-1.139	0.255	Same
Education								
High School Education or less	83	88.83	104	98.13	3887	-1.221	0.222	Same
Bachelors or higher	263	246.8	249	266.75	30191.5	-1.592	0.111	Same
Household Size								
1	63	69.25	72	66.9	2189	-0.359	0.719	Same
2	210	208.14	201	203.76	20655.5	-0.389	0.697	Same
3	93	95.83	107	104.56	4541.5	-1.116	0.264	Same
4	89	84.11	81	87.02	3481	-0.402	0.688	Same
5+	57	46.54	45	57.78	1000	-1.986	0.047	Different
Age								
18-24	71	67.2	69	73.9	2215	-1.02	0.308	Same
25-34	80	83.33	80	77.67	2973.5	-0.8	0.424	Same
35-44	92	97.87	97	92.28	4198	-0.738	0.461	Same
45-54	97	91.02	89	96.21	4075.5	-0.692	0.489	Same
55-64	91	86.79	81	86.17	3659	-0.085	0.932	Same
65-74	72	70.25	75	77.6	2430	-1.086	0.277	Same
75+	15	13.83	20	21.13	87.5	-2.19	0.029	Different
Region								
Upstate	125	134.61	144	135.34	8951	-0.08	0.936	Same
Midlands	169	156.41	150	164.05	12067.5	-0.769	0.442	Same
Lowcountry	119	123.73	127	123.28	7529	-0.051	0.959	Same
PeeDee	105	93.29	90	103.5	4230	-1.333	0.182	Same
Commute Length								
<10 minutes	46	53.38	57	50.89	1247.5	-0.443	0.658	Same
10-14	55	63.82	75	66.73	1970	-0.453	0.65	Same
15-19	69	57.92	46	58.12	1581.5	-0.033	0.974	Same
20-24	46	42.23	37	41.72	840.5	-0.1	0.921	Same
25-29	28	28.96	30	30	405	-0.247	0.805	Same
30-34	26	28.5	28	26.57	338	-0.47	0.638	Same
35-44	21	17.69	20	24.48	140.5	-1.895	0.058	Same
45-59	17	15.44	13	15.58	109.5	-0.044	0.965	Same
60+	16	11.44	9	15.78	47	-1.58	0.114	Same
Marital Status								
Married	287	277.18	278	289.01	38222	-0.897	0.37	Same
Single/Never Married	162	164.66	167	165.33	13472.5	-0.066	0.947	Same
Divorced	42	45.38	46	43.7	929	-0.319	0.749	Same
Separated	9	6.67	4	7.75	15	-0.475	0.634	Same
Unemployed	37	33.11	24	27.75	366	-1.214	0.225	Same
Widowed	18	16.5	16	18.63	126	-0.66	0.509	Same

Employment Status								
Employed Full time	261	263.84	264	262.17	34232.5	-0.132	0.895	Same
Employed Part time	74	59.36	48	64.8	1617.5	-0.873	0.383	Same
Retired	97	94.97	103	105.71	4459	-1.364	0.173	Same
Student	34	32.29	33	35.76	503	-0.753	0.451	Same
Homemaker	23	24.26	29	28.28	282	-1.009	0.313	Same
Unable to work	12	15.38	21	17.93	106.5	-0.772	0.44	Same
Community Type								
Urban	57	68.42	75	65.04	2028	-0.525	0.6	Same
Suburban	291	269.55	259	282.18	35954	-0.968	0.333	Same
Rural City/Town	86	92.54	103	97.05	4217.5	-0.587	0.557	Same
Rural	84	78.84	74	80.25	3052	-0.204	0.839	Same

Appendix C
Description of South Carolina Regions

According to SCDOT and SCDHEC, South Carolina can be divided into four unique regions, the Upstate, Midlands, Lowcountry, and Pee Dee regions.

- **Upstate Region**: Oconee, Pickens, Greenville, Spartanburg, Cherokee, Anderson, Union, Abbeville, Laurens, Greenwood, and McCormick Counties
- **Midlands Region**: York, Chester, Lancaster, Fairfield, Kershaw, Newberry, Lexington, Richland, Saluda, Edgefield, Aiken, and Barnwell Counties
- **Pee Dee Region**: Chesterfield, Marlboro, Dillon, Marion, Horry, Georgetown, Williamsburg, Florence, Williamsburg, Clarendon, Sumter, Lee, and Darlington Counties
- **Lowcountry Region**: Calhoun, Orangeburg, Bamberg, Dorchester, Berkeley, Charleston, Colleton, Beaufort, Jasper, Hampton, and Allendale Counties