Exploring the Potential of Using Privately-Owned, Self-Driving Autonomous Vehicles for Evacuation Assistance

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The potential use of privately-owned autonomous vehicles (AVs) for the evacuation of carless households threatened by hurricanes is underexplored. Based on 518 original survey responses from South Carolina (SC) residents, an ordered logistic model was developed to determine the willingness of individuals to temporarily share their AVs for evacuation without their presence. The model results indicated that respondents who (a) were unemployed, (b) had experience giving disaster relief assistance, (c) took regular religious trips and were more comfortable with AVs (d) delivering packages and (e) being purchased and shared for income in the next five years were more willing to share. Respondents who (a) were aged 65 or older, (b) had income below $25,000 per year, and (c) had less than two social media accounts were less willing to share. The model was applied to a state-wide synthetic population to simulate a disaster scenario in SC under different AV market penetration ($p$) scenarios to determine the potential use of AVs for evacuation assistance. Monte Carlo simulation results indicated that the percentage of households that can be evacuated increased linearly with respect to $p$, by 5.5% for every 1% increase in $p$ until $p$ was nearly 20%. When $p$ was 30% or higher, the number of shared AVs was sufficient to evacuate all households in need. Therefore, in SC, if privately-owned AVs are widely available, they could serve as a viable alternative or be used to supplement the traditional evacuation programs that rely on buses.

1. Introduction

In recent years, the southeastern U.S. has experienced strong hurricanes, from Hurricane Joaquin creating historic flood levels in Columbia, South Carolina in 2015 [1] to Hurricane Irma causing mass evacuations and hundreds of deaths [2] and Hurricane Florence causing record-setting flooding in the Carolinas [3]. The intensity and frequency of these storms are expected to increase [4]. The coastal population in the southeast is growing faster than any other region in the U.S. [5], indicating the potential for greater destruction from future storms. Combined with millennials having less desire to obtain a driver’s license and own a vehicle, these factors point to the greater need for government-assisted evacuations in the future [6]. This study explores a potential future government-assisted evacuation transportation system that relies on privately-owned, self-driving autonomous vehicles.

Hurricane Katrina (2005) highlighted deficiencies in the evacuation plans for vulnerable populations, including the carless [7]. Since then, the topic of evacuating the vulnerable population, specifically the carless, elderly, and special needs population, has grown in interest [8, 9]. Evacuation plans have evolved to address these segments of the population.

Currently, government-assisted evacuations for the carless and vulnerable populations typically rely on buses, which have high capacities to meet the potential demand for assistance. Across the country, transportation and emergency management agencies estimate an average of 6–10% of their population is classified as special needs and could use some form of assistance when ordered to evacuate for a
hurricane [10]. Those who could need assistance because of a lack of a readily-available vehicle represent approximately 8.7% of U.S. households, with this number expected to grow in the near future [11, 12]. South Carolina (SC) estimates that 5% of its population, or 49,000 residents, within evacuation zones would need assistance evacuating for a strengthening, category 5 storm. Currently, the State’s plan primarily involves transporting these evacuees by school buses to local shelters [13].

Transit is not the only option available to households lacking a reliable personal vehicle. Carpooling with peers is one alternative. In a study of Hurricane Lili evacuees, Lindell et al. [14] found that 9% obtained rides from family or friends. Based on a study using surveys from New York City, the largest transit commuting city in the U.S., researchers found a near-even split in carpooling (8% and 14%) and transit evacuation (12% and 16%) [15].

Other forms of shared vehicles for evacuation assistance have been considered recently. In the past five years, Uber and Lyft have helped people evacuate by offering ride vouchers [16]. In 2020, Florida’s Emergency Management Agency mentioned the use of Uber and Lyft to transport evacuees instead of mass transportation to minimize the spread of COVID-19 [17].

The potential future system envisioned in this paper goes beyond currently deployed technologies and is based on privately-owned autonomous vehicles (AVs). Upon a government official's announcement of receiving an official request for assistance from the public, some AV owners from around the state (or other geographic areas) would voluntarily and temporarily allow their vehicles to be used to assist with preimpact evacuation in designated evacuation zones, regardless of whether they would share their AVs for normal conditions. Thus, our use of the term “shared” (focusing on a temporary arrangement without the owner present) is slightly different from the mainstream interpretation of shared vehicles. The objective of this study is to explore the system's feasibility of using privately-owned AVs as a viable alternative or as a supplement to the traditional evacuation programs that rely on buses from the public’s willingness to share perspective (for this potential AV ownership future) and an evacuee demand coverage perspective for a hurricane in SC. To this end, this paper presents an ordinal logit model developed from original survey responses from SC residents to (1) determine the public’s willingness to let state and/or federal agencies use their AVs to assist others in evacuations and (2) identify factors that affect their willingness. The model is then applied to a synthetic SC population and used with simulation to determine what percentage of the critical transportation need (CTN) population can be evacuated, incorporating both the predicted level of the public’s willingness to share their AVs and different AV market penetration levels.

The remainder of this paper is divided into six sections. Section 2 reviews selected research on assisting carless evacuees and future AV adoption projections. Section 3 provides an overview of the survey data used to develop the ordinal logit model. Section 4 describes the ordinal logit modeling process, synthetic household generation, and simulation modeling background. Section 5 is the experimental design section, describing the factors tested during the simulation process. Section 6 discusses the results of the modeling process and experiments, including factors affecting willingness to share and the percentage of the CTN population that could be evacuated at different AV market penetration levels. Section 7 presents conclusions and future directions.

2. Literature Review

Many studies investigated the use of public transit vehicles and school buses to assist with mass evacuation. For example, Bish [18] developed an optimization model for regional evacuation planning as a variant of the vehicle routing problem. He assumed that the evacuees arrived at predetermined pickup locations at constant rates. Swamy et al. [19] implemented a simulation model which considered the dispatching of a given number of buses, stochastic arrivals of evacuees, queueing effects, and transport of evacuees to shelters. Naghawi and Wolshon [20] modeled and simulated transit-based evacuation strategies for the evacuation of the CTN population.

However, Renne et al. [7] stated that most cities do not have a sufficient number of buses to evacuate the entire CTN population. Moreover, buses cannot provide door-to-door services, which is an important consideration for those who cannot afford a ride to the pickup point. For these reasons, the recent work on mass evacuation of the CTN population has considered the use of ridesharing. Wong et al. [16] concluded that public agencies could leverage shared resources to assist with evacuation. Their study, which used survey responses from recent Hurricane Irma evacuees on a hypothetical future disaster, reported that 29.1% of evacuees would be willing to offer a ride to another evacuee before the evacuation process and 23.6% would be willing to offer a ride during the evacuation process. Li et al. [21] studied the utilization of shared vehicles for emergency evacuation under no-notice evacuation scenarios with limited time horizons. They performed numerical simulations to quantify the improvements in the total distance traveled and number of people evacuated. Naoum-Sawaya and Yu [22] addressed a problem in which individuals with vehicles are instructed to pick up others along their routes to evacuate the maximum number of individuals within a limited time. A mixed integer programming model was proposed to model the problem. Lu et al. [23] proposed a two-phase model that optimized trip planning and operations by integrating ride-sharing processes for short-notice evacuation situations. Their model jointly optimized the driver-rider matching and transfer connections among shared vehicle trips. These studies assumed the active participation of the vehicle’s driver/owner who was in the same area as the individuals needing assistance.

Many researchers consider AVs to be the next revolution in transportation. Bansal and Kockelman projected anywhere from 25% to 87% adoption of level 4 AVs, the lowest level AV able to drive without a human, by 2045 [24]. Another study projected that AVs would account for 20%–40% of the entire
vehicle fleet by the 2040s [25]. Yet another study projected anywhere from 15–90% adoption of AVs by 2050, depending on annual price reductions [26]. The most prominent cause for the slower adoption of AVs was considered to be the high cost [27]. The adoption increase with cost reduction was thoroughly discussed in [24]. AV adoption from a technology trust and ethics perspective was discussed in [28]. According to the study, human-machine interaction/integration needs significant investment to be able to achieve full trust in autonomous vehicles. Incidents in AVs or in other co-pilot-using systems indicated that sensor failures could lead to catastrophic events. However, there are additional factors to consider, such as increased risks in the case of incidents, complex nonuniform surroundings with ever-changing user behaviors, cyber vulnerabilities, and higher road construction costs [27, 29].

AV ownership was investigated by several researchers. AVs are expected to be expensive, and in the most optimistic scenario, only 35% of the survey respondents were willing to use shared AVs, while others prefer personal ownership [30, 31]. This is partly understandable, given the convenience of accessibility and being able to leave items in the vehicle. However, shared vehicles are predicted to be maintained better, to have higher security and to have less liability [27]. Regardless, Robinette et al. [31] showed that AV technology would reduce ownership by 1.1 vehicle but would result in a 13% increase in vehicle miles traveled (VMT) as unoccupied vehicles. This would also result as an increase in transportation energy usage and cause higher emissions. In [32], the authors discussed possible consequences of AV introduction with driving behavior and ownership changes. With personal AVs, the authors argued longer as well as unoccupied trips could be preferred by the owners. The authors also argued shared AVs can drive overall lower cost for vehicles. Redistribution of vehicles would also increase the number of trips per day. Many studies projected that AVs will be shared when implemented, similar to Uber and Lyft today [25, 33, 34]. These shared AVs could provide a transportation option that is significantly less expensive than taxi services and is convenient for citizens in urban areas [35]. However, to date, few studies have examined the potential use of self-driving AVs shared by the public to assist with mass evacuation and/or the potential of integrating shared-AVs into evacuation assistance systems.

AVs are expected to be widely adopted in the next 20–30 years indicating a need to examine their potential uses for evacuation. Though recent advances in technology point toward adoption in the near future, relatively little has been studied regarding their potential use in evacuation situations. However, for connected vehicles (CVs), Yin et al. designed an application that helps vulnerable households evacuate by providing pickup time and location options, optimizing route guidance to reduce congestion, and locating food and fuel along their route [36]. Our study explores the use of temporarily shared AVs to assist SC CTN households evacuate from a hurricane. The integration of shared AVs could aid in the service gap (e.g., door-to-door service) that public transit vehicles do not provide. Without the limitation of only picking up evacuees from a few selected pickup points, shared AVs could provide more personalized pickups for the vulnerable population that has challenges reaching those pickup points.

This study addresses gaps in extant knowledge. First, it builds on the limited body of work addressing the potential use of AVs for evacuation by considering self-driving AVs rather than vehicles shared by driver-owners. This requires an examination of willingness to share a personally-owned vehicle without being physically present. Second, the potential of a self-driving AV assistance program to replace a bus-based system is examined, addressing issues associated with insufficient resources and last-mile issues as well as the established preference for using personal vehicles to evacuate rather than transit-based options (see for example [37]).

3. Survey Data Overview

To gauge the public’s willingness to share their future, driverless AVs to help evacuate an area before a hurricane makes landfall, the research team developed a survey; the survey questions were formed and guided by three focus group sessions. This survey was implemented using Qualtrics Panels and distributed to SC residents across the state. A total of 1,050 responses were received, split evenly between two scenarios: evacuation (used in this manuscript) and disaster relief. The age and gender splits of the respondents were representative of SC demographics, according to the American Community Survey (ACS) [38]. However, the sample had an intentionally slightly higher number of individuals with income above the median and higher number of individuals with education above a high school degree. This slight oversampling was performed to adequately capture demographic categories more likely to be able to afford future AVs [25, 34, 39]. After data cleaning, the final dataset used for the ordered logit model had 518 responses.

The survey placed respondents in a scenario where they considered temporarily sharing a personally-owned, driverless AV for use in an evacuation, where their local area was not affected. The Likert-type question of how willing (extremely willing (15%), willing (21%), somewhat willing (23%), neither willing nor unwilling (10%), somewhat unwilling (7%), unwilling (10%), and extremely unwilling (14%)) respondents were to share in this context was used as the dependent variable in an ordinal logit model. The extremely willing/willing and extremely unwilling/unwilling categories were combined to condense the data to five ordered categories. However, this does not affect any ordered categories not involved in the category combination [40]. To determine factors associated with greater willingness to share, the survey also asked respondents about existing travel habits, current vehicle technology, general technology adoption, experience with the sharing economy, experience giving and volunteering, experience with natural disasters, comfort with autonomous vehicles, and demographic characteristics. Table 1 provides summary statistics of selected variables and the single-variable ordered logit models between the variable and willingness to share a personal vehicle for evacuation assistance.
4. Methodology

The methodology consisted of two major components: estimating the availability of AVs to transport evacuees from SC coastal evacuation zones and determining the degree to which these AVs met the anticipated evacuee demand.

4.1. Estimating AV Availability. Estimating the AV availability involved two steps. First, an ordered logit model was developed from the survey data. Second, this model was applied to a synthetic population generated based on Census data. The dependent variable for this model was a five-point Likert-type question asking respondents to rate their willingness to share a personally-owned AV to help others evacuate from a hurricane. Ordered logit models containing multiple explanatory variables can be written as in the following equation:

\[
\ln(\pi_j) = a_j - (\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n),
\]

where \(x_1, x_2, \ldots, x_n\) are the explanatory variables, \(\pi_j = p(\text{score} \leq j)/p(\text{score} > j)\), \(a_j\) is the intercept of the logit \(j\), and \(\beta_1, \beta_2, \ldots, \beta_n\) are the regression coefficients of each explanatory variable [41]. The ordered logit model's proportional odds assumption was tested using the Parallel Line Test, which ensured that the slope coefficients were the same across all categories [42, 43]. The model was created using a manual forward stepwise process [44] with the variables' entering order based on the \(p\)-values arising from ordered logit models developed using each variable individually (see Table 1). Improvement to the model was determined by an increase in the McFadden Pseudo R-Square value as well as a 95% confidence level that the parameter estimates were significantly different from zero. This process was repeated until reaching the individual variable significance level of 0.25, as recommended for large sample sizes [45].

The ordered logit model (see Table 2) was then applied to a synthetic population of SC to obtain a spatially distributed number of AVs available for evacuation assistance. The population synthesis process expands a seed population of SC to obtain a spatially distributed number of AVs available for evacuation assistance. The regional control was set to the number

### Table 1: Summary statistics of selected variables and relationship with evacuation sharing variable

| Variable | Total \(n\) | Min | Max | Mean | S. dev | Parameters | S. err |
|----------|-------------|-----|-----|------|--------|------------|-------|
| Dependent variable | | | | | | | |
| Willingness to share AV for evacuation | 518 | 1 | 5 | 3.409 | 1.603 | — | — |
| Independent variables | | | | | | | |
| Demographics | | | | | | | |
| Gender: women | 518 | 0 | 1 | 0.494 | 0.500 | 0.038 | 0.158 |
| High income (>$100,000 per year) | 518 | 0 | 1 | 0.288 | 0.453 | −0.120 | 0.175 |
| Household size | 512 | 1 | 5 | 2.740 | 1.207 | 0.010 | 0.066 |
| Educated with a 4-year degree or more | 518 | 0 | 1 | 0.508 | 0.500 | 0.008 | 0.158 |
| Age 65 or older | 518 | 0 | 1 | 0.168 | 0.374 | −0.754 | 0.213 |
| Income under $15,000 per year | 518 | 0 | 1 | 0.077 | 0.267 | −0.504 | 0.296 |
| Unemployed | 518 | 0 | 1 | 0.071 | 0.258 | 0.646 | 0.320 |
| Race: white/caucasian | 518 | 0 | 1 | 0.494 | 0.500 | 0.038 | 0.158 |
| Living in urban area | 518 | 0 | 1 | 0.110 | 0.313 | 0.202 | 0.255 |
| Technology | | | | | | | |
| Use of ride-hailing services 8+ times in past year | 518 | 0 | 1 | 0.168 | 0.374 | 0.671 | 0.219 |
| 0 or 1 social media accounts | 512 | 1 | 5 | 2.740 | 1.207 | 0.010 | 0.066 |
| High comfort in AV deliveries in 5 years | 518 | 0 | 1 | 0.508 | 0.500 | 0.008 | 0.158 |
| High comfort in sharing AV for income in 5 years | 518 | 0 | 1 | 0.168 | 0.374 | −0.754 | 0.213 |
| High number of technology features on newest vehicle | 518 | 0 | 1 | 0.168 | 0.374 | 0.671 | 0.219 |
| Evacuation experience | | | | | | | |
| Household evacuation experience | 518 | 0 | 1 | 0.322 | 0.468 | 0.105 | 0.170 |
| Experience evacuating with friends/family | 167 | 0 | 1 | 0.144 | 0.352 | 1.925 | 0.498 |
| Received evacuation assistance from friends/family | 167 | 0 | 1 | 0.329 | 0.471 | 1.346 | 0.321 |
| Giving and volunteering | | | | | | | |
| Giving to charitable causes more than once per year | 518 | 0 | 1 | 0.635 | 0.482 | 0.382 | 0.165 |
| Volunteering more than once per year | 518 | 0 | 1 | 0.508 | 0.500 | 0.527 | 0.160 |
| Experience giving any disaster relief assistance | 518 | 0 | 1 | 0.629 | 0.483 | 1.070 | 0.168 |
| Experience giving to assist friends/family in disaster relief efforts | 518 | 0 | 1 | 0.259 | 0.438 | 0.514 | 0.184 |
| Takes religious trips during a typical week | 518 | 0 | 1 | 0.334 | 0.472 | 0.458 | 0.170 |
| Commuting | | | | | | | |
| Commuting by single-occupancy vehicle | 335 | 0 | 1 | 0.833 | 0.374 | −0.281 | 0.267 |
| Commute length | 324 | 10 | 60 | 23.386 | 13.825 | −0.005 | 0.007 |
| Regular weekly commute schedule | 335 | 0 | 1 | 0.684 | 0.466 | −0.126 | 0.213 |

Note: ***\(p < 0.001\), **\(p < 0.05\), and *\(p < 0.1\).
of people in each subcounty using ACS 2018. The PUMS data was contained in the Public Use Microdata Areas (PUMA), which are geographic units containing no fewer than 100,000 people each. The desired spatial resolution for this study was the subcounty area, which was smaller than the PUMA. The PopulationSim package in the Python environment bridged the gap between the two geographic levels and produced the synthetic population at the subcounty level [47]. The resulting synthetic population had 1,894,711 households which was the exact number from the 5-year estimates of households from 2014–2018 ACS data. Demographic variables age, income, and employment status, statistically significant in the ordered logit model, were also generated for each household during the population synthesis process. These variables were then recoded into binary indicator variables for model application. Other non-demographic variables needed for the model were generated using the observed distribution from the survey (see Table 1). Based on equation (1), the probability of each outcome was calculated using the following equation [40]:

\[
p(score = j) = \pi_j - \pi_{j-1}. \tag{2}\]

4.2. Estimating the Ability to Meet Evacuation Assistance Demand. To determine how many critical transportation need households (CTNH) could be evacuated from the evacuation zones using AVs shared by the public, a Monte Carlo simulation model was developed. The simulation model required the following input data: percentage of SC citizens willing to share their AVs to assist with evacuation (output from the ordered logit model using a synthetic SC population), percentage of AV market penetration (see Table 3), total population in an evacuation zone [48], total population in a nonevacuation zone [49], percentage of the CTN population that needed to be evacuated [50], distribution of time for which an AV would be available (survey data from this study), average speed of AVs during evacuation [51], shelter locations [50], average number of people per household [52], a GIS map of SC at the subcounty level [53], and a GIS map of evacuation zones [48].

The model’s primary output was the covered demand ratio (CDR), which was obtained by dividing the number of CTNH evacuated from the evacuation zones using AVs by the total number of CTNH. Figure 1 presents the logic implemented in the Monte Carlo simulation model which was implemented with the following assumptions:

1. AVs were only available in the nonevacuation region.
2. One household had only one AV.
3. One AV evacuated one CTNH in a single trip.
4. All AVs available in a subcounty started and ended their trips at the centroid of that subcounty.
5. All evacuees in an evacuation zone were picked up at the centroid of that evacuation zone.

As shown in Figure 1, in Step 1, the model read the input data mentioned above. Among the input data were the CTNH that need to be evacuated from an evacuation zone (shown in gray in Figure 2) and brought to a shelter located in the nonevacuation zone (shown in white in Figure 2). In this study, the evacuation zones considered were those defined by the South Carolina Emergency Management Division based on their vulnerability to hurricanes. In all, there were 20 zones in the evacuation region. Instead of using the exact home address of the CTNH as the pickup location, without loss of generality, this study used the centroid of the zone as the pickup location. The start and end location of each AV were also assumed to be at the centroid of the nonevacuation zone. The spatial scale chosen for the nonevacuation zone was the census county division level, referred to as “subcounties” hereafter. This was chosen to be consistent with the spatial scale used by the logit model. Subcounties consist of incorporated cities, boroughs, and towns. Geographically, a subcounty is larger than a census

| Parameter estimate | Standard error | Significance |
|--------------------|----------------|-------------|
| Age 65 or older    | -0.531         | 0.228       | 0.020       |
| Income under $15,000 per year | -0.728 | 0.333 | 0.029 |
| Unemployed         | 1.219          | 0.357       | 0.001       |
| Takes religious trips during a typical week | 0.374 | 0.178 | 0.035 |
| 0 or 1 social media accounts | -0.540 | 0.213 | 0.011 |
| High comfort in AV deliveries in 5 years | 0.747 | 0.172 | 0.000 |
| High comfort in sharing AV for income in 5 years | 0.604 | 0.296 | 0.042 |
| Experience giving any disaster relief assistance | 0.886 | 0.180 | 0.000 |

| Number of responses | 518 |
|---------------------|-----|
| McFadden Pseudo R-Square | 0.072 |
| Adjusted McFadden Pseudo R-Square | 0.067 |
| Parallel line test (0.549) | Pass |
| Number of variables | 8 |
block but smaller than a county. In all, there were 265 zones in the nonevacuation region. The shelter locations were actual locations, not centroids of nonevacuation zones. In Step 2, the model calculated the number of AVs available in the nonevacuation region and the number of CTNH in the evacuation region requiring assistance. The number of AVs available in each subcounty was calculated using equation (3). The sum of this number for all subcounties in the nonevacuation region gave the total number of AVs available in SC for evacuation. The number of CTNH in each evacuation zone was calculated using equation (4). The sum of this number for all evacuation zones gave the total number of CTNH:

\[ n = \left( \frac{p}{100} \right) \times \left( \frac{s}{100} \right) \times h, \]

where \( n \) = number of AVs available in a subcounty, \( p \) = percentage of AV market penetration, \( s \) = percentage of households willing to share their AVs for emergency evacuation, and \( h \) = number of households in a subcounty.

\[ np = \left( \frac{pp}{hs} \right) \times \left( \frac{pc}{100} \right), \]

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

In Step 3, the time (i.e., duration) for which each AV was available was obtained from a discrete distribution; this distribution was generated from survey response data (see Figure 3). In Step 4, given the AV time availability, the
maximum distance (in miles) for which an AV was available was calculated using the following equation:

\[ d = t \times v. \]  

(5)

In Step 5, an AV was randomly selected from the pool of available AVs. Available distance for the selected AV was the maximum distance calculated using equation (5). If the available distance was sufficient to evacuate the nearest CTNH, then the model simulated the AV going to the nearest CTNH and dropping the CTNH off at the nearest shelter. This process for the selected AV was repeated until its time/distance availability was exhausted. The model then selected another AV and repeated this process until either all CTNH were evacuated or no more AVs were available. In Step 6, the CDR was calculated using the following equation:

\[ \text{CDR} = \frac{\text{Number of CTNH evacuated}}{\text{Total number of CTNH}}. \]  

(6)

5. Simulation Scenarios

To determine what percentage of the CTNH could be evacuated (i.e., CDR) at the predicted public’s willingness to share their AVs to assist with the evacuation, the developed Monte Carlo simulation was used. The model was run for four AV market penetration scenarios obtained from Bansal and Kockelman [24]. The AV market penetration for future years under each scenario is shown with the results in Table 3. Scenario 3 represented the most conservative estimate of AV market penetration whereas Scenario 8 represented the most optimistic. These scenarios were based on the projected annual increase in the willingness to pay (WTP), annual drops in technology price, and changes in government regulations. Scenario 1 was with constant WTP, 10% drop in the technology price, and no regulations. Scenario 3 was with 0% but no-zero WTP, 10% drop in the technology price, and no regulations; in this scenario, the tenth percentile WTP (among nonzero WTP individuals) for the individual’s household-demographic cohort was used. Scenario 6 was with 5% annual increase in WTP, 10% drop in the technology price, and with regulations. Scenario 8 was with 10% annual increase in WTP, 10% drop in the technology price, and with regulations [24].

The experiments assumed a category 5 hurricane. As such, the percentage of CTN used was 5% based on findings from the State of South Carolina CTN Evacuation Operations Plan [13]. The SC population was assumed to be 5.1 million, and the number of occupied homes was assumed to be 2.3 million based on the most recent Census data [54].

The time for which an AV was available was randomly drawn from the developed discrete distribution shown in Figure 3. It was assumed that 70% of the evacuees evacuated during the day and 30% evacuated during the night [55]. The average speed for the AV during evacuation was assumed to be 20 mi/hr during the day and 40 mi/hr during the night based on archived speeds along SC highways during the past six hurricanes [50].

6. Results and Discussion

6.1. Ordered Logit Model Results. The final ordered logit model contained 518 observations and had an adjusted McFadden Pseudo R-Square of 0.067, within the 0.012 to 0.138 range found in previous studies [56]. In this model, negative coefficients signified a lower willingness to share [40]. The model shown in Table 2 had eight statistically significant variables with age 65 or older, income under $15,000 per year, and 0 or 1 social media accounts being negatively associated with willingness to share, meaning that...
individuals with these characteristics were less likely to share their AVs to assist with evacuation. Being unemployed, taking regular religious trips, having high comfort in AV deliveries in five years, having high comfort in sharing an AV for income in 5 years, and having any experience giving for disaster relief were positively associated with willingness to share.

The model in Table 2 was then applied to the synthetic population. The probability of selecting a 5, which represented the maximum willingness to share an AV, was recorded for each household in SC. This probability was then aggregated based on each subcounty. The overall probability of selecting a 5 for all subcounties had a mean of 32.02% and standard deviation of 0.6%.

6.2. Simulation Modeling Results. The results of the simulation experiments, averaged over 15 runs, are shown in Table 3. At the projected AV penetration level in 2025, 29% (scenario 3) to 87.5% (scenario 8) of the CTNH could be evacuated. By 2040, 88.8% could be evacuated in the most pessimistic scenario and 100% in the most optimistic scenario. It should be noted that these projections were done in 2017 [24]. At the present time, year 2020, it is clear that the deployment of level 4 AVs is still many years away from becoming a reality.

Figure 4 shows the relationship between the covered demand ratio (CDR) and AV market penetration (p). These results indicated that the CDR increased linearly with respect to AV market penetration, up to about 20%, beyond which the relationship resembled a concave function. For scenarios 1, 3, and 8, CDR was approximately 0.9 at 20% AV market penetration. That meant 90% of the CNTH could be evacuated if the AV market penetration was 20%. For scenario 6, at 20% market penetration, approximately 85% of the CNTH could be evacuated. At 30% AV market penetration and beyond, the number of shared AVs was sufficient to evacuate all the required CTNH. These results were in agreement with the Pareto principle [57]: 80% of CTNH could be evacuated with 20% AV market penetration.

Figure 5 provides four alternative models that could be used to determine what market penetration level would be needed to be able to cover a certain evacuation demand: polynomial, logistic, exponential, and hyperbolic tangent. 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. The logistic regression model had a more complex form compared to the polynomial model, but its advantage was that it could be used for any \(0 \leq p \leq 100\%\). The polynomial regression model can only be used when \(p \leq 28\%\). 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. The CDR increased linearly with respect to AV market penetration up to about 20%. Beyond 20%, AV market penetration had less effect on the covered demand ratio:

\[
CDR = \begin{cases} 
-19.89p^3 - 1.59p^2 + 5.58p, & p \leq 28\% \\
1.0, & \text{o.w.} 
\end{cases} 
\]  

A 3rd order polynomial model was given in equation (7) which was able to express the CDR within 1.2% RMSE.

\[
CDR = \frac{e^{0.43p} - e^{-0.43p}}{e^{0.43p} + e^{-0.43p}}, \quad 0 \leq p \leq 100\%.
\]  

The hyperbolic tangent (tanh) model in equation (8) can estimate CDR within 3.2% RMSE.

\[
CDR = 1 - \frac{9.96}{1 + 4.33^{8.73 + 0.08p - 0.00234p^2 + 0.000021p^3}}, \quad 0 \leq p \leq 100\%.
\]  

The logistic regression model in equation (9) can estimate CDR within 1.2% RMSE.

\[
CDR = 1 - e^{-18.01p} - 18.01pe^{-18.01p}, \quad 0 \leq p \leq 100\%.
\]
The exponential model in equation (10) can estimate CDR within 2.6% RMSE.

7. Conclusions

This manuscript explored voluntarily, temporarily shared, privately-owned, and driverless autonomous vehicles for assistance with hurricane evacuations. Using original survey data from South Carolina residents, an ordered logit model was developed to determine the willingness to share privately-owned autonomous vehicles and factors affecting this willingness to share. The model’s significant variables indicated that respondents aged 65 or older, respondents with income under $15,000 per year, and respondents with 0 or 1 social media accounts were less likely to share their AVs to assist with evacuation. On the contrary, being unemployed, taking regular religious trips, having high comfort in AV deliveries in five years, having high comfort in sharing an AV for income in five years, and having any experience giving for disaster relief were positively associated with willingness to share.

When the ordered logit model was applied to the synthetic SC population, approximately 32% of households were willing to share their AVs to assist with hurricane evacuation. Based on this estimate, a Monte Carlo simulation model was used to determine the ability of the AV sharing system to meet CTNH needs for evacuations. When the AV market penetration was 30% or higher, the model indicated that the number of shared AVs would be sufficient to evacuate all households in need, given the potential AV ownership future examined in this study.

This study suggests that such a future evacuation assistance system has the potential to be successful, although many details will have to be considered in the future and initial trials would have to be run in conjunction with current methods of transporting vulnerable populations. It is important to note the potential limitations on the use of this paper’s results. First, AVs are not widely owned yet, necessitating that the survey be stated preference for a novel topic; thus, there was the potential for overenthusiasm in volunteering to share personally owned, driverless AVs as well as possible complications in fully understanding the survey topics. Second, multiple possible AV ownership futures exist, some of which include a shift from personally owned vehicles to subscription service, which would impact the availability of AVs for evacuation assistance. To manage the length of the paper, this study addressed only one potential future here, but future efforts will explore the subscription service as well with the public’s tolerance for service delays. Third, current populations and demographics were used, which may or may not conform with those corresponding to the future AV market penetration rates. Fourth, the details of how evacuation travel assistance could be requested were not part of this study; this would have to be determined in the next step of more rigorously identifying the demand side of the issue and the matching of demand with the available supply. Fifth, the evacuation speeds were assumed to be 20 mi/hr during the day and 40 mi/hr during the night. Sixth, it was assumed that one AV can evacuate an entire household. Seventh, for simplicity, the centroid of the evacuation zone was assumed to be the CTNH pickup location, and the centroid of the nonevacuation zone was assumed to be the starting and ending locations of AVs.

In addition to those mentioned above, a number of research areas could be pursued in the future. First, the survey could be applied to other states or hurricane-prone counties to determine the feasibility of this type of the system in other disaster-prone areas. Also, future surveys of this type could delve into potential limitations on sharing such as compensation desires as well as comfort levels of those potentially needing this evacuation assistance. Future studies could also examine different potential AV ownership scenarios and incorporate the system into larger evacuation simulations.

Data Availability

The survey data used to support the findings of this study are available from the corresponding author upon request. The data in the simulation are available from both the corresponding author and C2M2.

Disclosure

The authors are solely responsible for the content of this paper.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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