The Impacts and Adoption of Connected and Automated Vehicles in Tennessee

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16. Abstract

Connected and autonomous vehicles (CAVs) can revolutionize the daily travel modes, personal, public, or shared mobility because of technology-assisted driving. However, such a revolution will come at the cost of numerous anticipated barriers like accident liabilities, data safety concerns, the addition of new infrastructure, and increased emissions because of the induced travel demand. Adoption research from non-transportation related innovation suggests that social network plays a pivotal role in deciding whether to adopt, defer, or not to adopt. The existing literature in capturing the individuals' intention to adopt autonomous vehicles based on their social network is limited. Hence, this research aims to understand, model, and predict CAV market penetration in Tennessee based on residents' social network. Based on the statewide survey responses of 4,602 Tennesseans, a hybrid choice model was modeled to capture the impact of attitudes and perception on their intention to adopt CAVs. An agent-based model was also rendered to capture the impact of peer-to-peer interaction and the price of CAVs on their future adoption. Key findings highlight the positive impact of residents' perceptions towards their social status, input received from their peers, tech-savvy lifestyle, and willingness to pay more towards autonomous technology on their intention to adopt personally owned-CAVs. Finally, adoption forecasts showed higher levels in four major counties of Tennessee, and an annual price reduction of 20% can increase the adoption rate by 17 times. Based on these findings and COVID-19 impacts on CAVs, this research proposes some recommendations to help planners boost the adoption of CAVs through policies focusing on infrastructure, subsidies, and advertisement.

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Executive Summary

In 2017, in the United States (US), the transportation sector was responsible for 39,141 fatalities, and ~89% of these fatalities were because of driver-related errors where impaired driving and speeding were among the major causes (~32% and ~29% respectively). In addition to eliminating all human error-related accidents, Connected and Autonomous Vehicles (CAVs) can revolutionize the way we travel through increased productivity during travel. However, there are some anticipated negative impacts of CAVs like virus attacks, hacking, data privacy, and cybersecurity. Despite the commitments from governments and industries in allowing open road CAV testing and investing in development to push CAV's market penetration by 2025, their user acceptance is still uncertain. It will be a paradigm shift for the general population to switch to CAVs from conventional vehicles even if CAVs meet their expectations and provide increased utility. The state of Tennessee welcomes CAVs for testing and operation on public roads, making it more important to study the anticipated adoption of CAV in the state. Existing research indicates the importance of peer-to-peer interaction on the acceptance of novel technological innovations. However, recent research on CAV adoption fails to capture such impacts. Hence, this project modeled a fusion of agent-based and hybrid choice models that can capture the impact of word-of-mouth (peer-to-peer interaction) and perceptions towards CAV-related positive and negative impacts. The model is also capable of forecasting the future market share of CAVs for the state of Tennessee.

A comprehensive review on international and national studies on CAVs was covered. Based on the methodological approaches, all studies were segregated into two major groups, i.e., aggregate and disaggregate. An online survey in Tennessee was then conducted to collect over 4,602 complete responses through three different survey distribution channels (Amazon Mechanical Turk, market research company panel, and a combination of both social media and educational institutes in Tennessee). The survey asked questions related to individuals' perceptions towards CAVs based on the influence from their social network and concerns towards positive and negative aspects of CAVs. R-Shiny web dashboard was then developed to showcase the survey results to a larger population (click here to access). The survey dataset was then expanded to the entire state after generating a synthetic population through PopGen software utilizing age, gender, and ethnicity as the matching variables between the survey dataset and population forecasts for Tennessee.

The hybrid choice model with an ordered logit framework was estimated based on the survey dataset to capture residents' perceptions towards CAVs and inclination to adopt five different CAV-based travel modes: privately owned, carpool, public transport, and ride-hailing service with and without the human backup driver. The model included two different parts, i.e., structural equation modeling and discrete choice modeling. Structural equation modeling identified and estimated the attitudinal constructs associated with the acceptance of CAVs and their relationship with peer-to-peer interaction. Six attitudinal constructs identified were: Social Status, Social Influence, CAV Benefits, CAV Barriers, CAV Purchase, and Media Influence. Discrete choice modeling estimated the residents' likelihood of adopting various CAV-based travel modes based on attitudinal constructs, travel behavior, and peer-to-peer interaction attributes. The adoption was measured on three different levels: "Fully Adopt, "interested, and "Reject." Then the agent-based model was simulated to capture the impact of peer-to-peer interaction (word-of-mouth)

on the adoption decision of an individual. Four different scenarios were considered for the annual price reduction of CAVs (5% to 20% with a step size of 5%). Previously trained hybrid choice model and agent-based model results were then applied to a synthetic population dataset to forecast the proportion of population adopting CAV over time based on their income levels and price reduction of CAVs. The adoption forecasts were then provided for all five CAV-based travel modes at the statewide and county levels. Policy implications were identified based on the key findings, and COVID-19 impacts were also explored.

Key Findings

- Residents of all ages and income levels are concerned about all six attitudinal constructs, highlighting the importance of peer-to-peer interaction, media advertisements, and factors including positive, negative, and purchase characteristics of CAVs.
- Individuals with increased social ties are associated with higher level of concern towards social status and influence from their peers if they choose to adopt CAVs. Individuals who do not receive any CAV-related information from their peers rely on media advertisements.
- Individuals willing to pay higher for autonomous technology, familiar with current smart technologies, and concerned about all six attitudinal constructs are more likely to adopt all five CAV-based travel modes. In contrast, the elderly and individuals who bought two or more cars in the last ten years were less likely to own CAVs.
- Among the adoption forecasts, the proportion of individuals deciding to accept CAVs was significantly less for those interested in adopting but have not adopted yet. The adoption forecasts are highest for privately owned CAVs, especially in four major counties of Tennessee. Although the CAV's annual price reduction increases the adoption rate by about 18 times, the adoption rate is still low in the majority of counties,

Key Recommendations

- There is a need to for public awareness strategies through social media and media channels in the initial stages of CAVs (as per the positive relationship of all attitudinal constructs on adoption). The target population can include residents planning to buy or sell a car in the next three years, up to date with latest smart technology, and willing to pay higher for autonomous technology for the wider acceptance of personally-owned CAVs.
- The increased sensitivity of CAV adoption with their price calls for a need to offer incentives to early adopters. Incentives can be offered in tax rebates, reduced registration costs, and discounts in annual renewals. Integrating CAVs with existing infrastructure and intelligent transportation systems like TDOT SmartWay will decrease the operational cost of CAVs and, hence, decreasing their price.
- Public awareness strategies focusing on shared-mobility based CAVs have a potential of ensuring safer, fast, and environment-friendly highways in Tennessee.
- Lessons can be learned from the successful implementation of CAVs in the contactless delivery of goods during the COVID-19 pandemic to reduce the negative perceptions of CAVs to ensure higher acceptance rates while increasing the proportion of early buyers.

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Glossary of Key Terms and Acronyms

Acronym	Description
ABM	Agent Based Modeling
ACS	American Community Survey
CAV	Connected and Autonomous Vehicle
CFI	Comparative Fit Index
DCM	Discrete Choice Modeling
EFA	Exploratory Factor Analysis
HCM	Hybrid Choice Modeling
HIT	Human Intelligence Task
IRB	Institutional Review Board
MSL	Maximum Simulated Likelihood
NHTSA	National Highway Traffic Safety Administration
SEM	Structural Equation Modeling
OL	Ordinal Logit
SAE	Society of Automotive Engineers
SP	Stated Preference
SRMR	Standardized Root Mean Square Residual
RMSEA	Root Mean Square Error of Approximation
RP	Revealed Preference
TLI	Tucker Lewis Index
WOM	Word-of-mouth
WTP	Willingness to Pay

Chapter 1 Introduction

In 2017, in the United States (US), the transportation sector was responsible for 39,141 fatalities, and ~89% of these fatalities were because of driver-related errors where impaired driving and speeding were among the major causes (~32% and ~29% respectively) (USDoT, 2018). Connected and autonomous vehicles (CAVs) have the potential of eliminating all such human error-related accidents. (D. J. Fagnant & Kockelman, 2015; Gurney, 2013) as such vehicles will not require a human for the driving operation. Society of Automotive Engineers (SAE) and National Highway Traffic Safety Administration (NHTSA) define five levels of vehicle automation, with the lowest being no automation and the highest being full automation (NHTSA, 2018).

Among other benefits, CAVs will provide increased productivity during travel, flexibility in living farther away from urban areas, travel time savings (congestion and parking), and increased mobility to the elderly, physically challenged, and non-license holder individuals. CAVs will also include some negative impacts related to virus attacks, privacy, accident-related liabilities, cybersecurity, giving up driving, and increased emissions levels due to induced demand (Gkartzonikas & Gkritza, 2019; Milakis, 2019). In the US, almost every state has passed legislation for the testing and operating CAVs on public roads (NCSL, 2020; Talebian et al., 2019). Also, major automaker companies are committed to investing billions of dollars in the research and development of CAVs to make the CAVs available to the general public (Jon Walker, 2018). For instance, General Motors has already acquired self-driving car startup Cruise automation and a 9% stake in ride-hailing service Lyft. Ford has acquired Argo AI (robotics company) and plans to launch level 4 autonomous vehicles by 2021. Similarly, Honda, Toyota, Renault- Nissan, Volvo, Hyundai and Daimler have made it clear to introduce AVs from 2020 onwards (Jon Walker, 2018). However, such commitments from governments and automakers will not be enough as it will be more of a paradigm shift for the general population to give up conventional vehicles for CAVs.

Past literature vindicates that vehicle ownership represents individuals' social status among their peers (Helveston et al., 2015) and has a direct impact on their travel behavior (Nielsen & Haustein, 2018; Zmud et al., 2016). The literature also highlights the link between the information received from individuals' social networks (Cheung et al., 2014; Venkatesh et al., 2003; X. Wang et al., 2012) and media advertisements (Nielson, 2015), collectively known as word-of-mouth, on their intention to choose novel technological innovations like CAVs. Prolific literature exists on exploring the acceptance and market penetration of CAVs through different methodological approaches like the Bass model (Shabanpour, Shamshiripour, et al., 2018), discrete choice models (DCM) (Bansal et al., 2016; Bansal & Kockelman, 2017; El Zarwi et al., 2017; Jiang et al., 2019; Lavieri et al., 2017; Nair et al., 2018; Nazari et al., 2018; Shabanpour et al., 2017; Shabanpour, Golshani, et al., 2018; Shin et al., 2015; Spurlock et al., 2019), structural equation models (SEM) (Abraham et al., 2017; Asgari & Jin, 2019; Kaur & Rampersad, 2018; Leicht et al., 2018; Liu, Guo, et al., 2019; Liu, Yang, et al., 2019; Pettigrew et al., 2019), and other miscellaneous types of models including correlation analysis, regression analysis, and analysis of variance (Hohenberger et al., 2016; Kyriakidis et al., 2015; Liljamo et al., 2018; Nordhoff et al., 2018; Piao et al., 2016; Sanbonmatsu et al., 2018; Schoettle & Sivak, 2014a, 2014b; Simpson et al., 2019; Simpson & Mishra, 2020; S. Wang & Zhao, 2019; Xu & Fan, 2019). However, all such studies fail to capture the impact of CAV-related information received from their social networks and media channels or do not provide market share forecasts. In addition, traditional DCMs, dominating the existing research, fail to capture the perceptions, attitudes and social impacts on the acceptance of CAVs (Atasoy et al., 2013; Kim et al., 2014).

The state of Tennessee welcomes CAVs to public roads with the enactment of the Automated Vehicles Act (Tennessee State Capitol, 2017). However, compared to other US states, approximately 93% of the state is rural, and residents rely heavily on private cars to complete their daily travel-related needs. This calls for a need to explore the potential future of CAVs in Tennessee, considering the residents' perceptions of technological innovations like vehicle automation and the existing conventional vehicles. Hence, building upon the existing literature, the objectives of this project are:

1. To explore the current status of literature, focusing on methodological approaches on the consumer's perceptions and preferences towards CAVs and the anticipated market share of CAVs.
2. To design and conduct a statewide survey to record the residents' perceptions, barriers, and adoption preferences towards CAVs (including privately owned and shared mobility).
3. To analyze the survey responses and expand these to the entire population of Tennessee through the synthetic population.
4. To explore the impact of peers in social network, social status, and positive and negative impacts of CAVs on their anticipated adoption of CAVs.
5. To forecast and showcase CAV adoption levels at both state and county level
6. To Identify the key policy implications based on the modeling and adoption forecasts and propose recommendations to boost the acceptance of CAVs in Tennessee.
7. To explore the present status of CAVs in the context of COVID-19 and propose additional recommendations to counter the uncertainties.

To achieve these objectives, first, a survey was conducted in Tennessee to ask residents their perceptions and preferences towards autonomous vehicle technologies and the anticipated impact of such technologies on their social network. After analyzing the survey responses, a web dashboard was developed to showcase the results to a larger population. The survey results were then expanded to the entire population of Tennessee using synthetic population. A fusion of the hybrid choice model with the agent-based model was then used to forecast the market share of CAVs by 2050. The project is concluded with key policy implications and final recommendations, based on the results and COVID-19 impacts, to increase the adoption CAVs in the state of Tennessee.

The rest of the report is organized as follows. Chapter 2 presents the literature review of various national and international studies covering CAV adoption and market share forecasts. Chapter 3 describes the survey data, including the design, methodology, collection, and data analysis. Chapter 4 provides the methodological approaches utilized in the project with their mathematical formulation and steps involved. Chapter 5 scrutinizes the results and identifies the key policy implications. Chapter 6 concludes the project with important recommendations.

Chapter 2 Literature Review

This section includes the methodological framework and significant findings of previous studies related to capturing the intention or likelihood to own/adopt and the impact of social influence on the likelihood to adopt CAVs. The literature is limited in covering a comprehensive review of methods employed for predicting autonomous vehicle adoption (Berrada & Leurent, 2017; Clark et al., 2016). Berrada and Leurent (2017) covered the modeling studies employed to study all the aspects of autonomous vehicles rather than their adoption. Clark et al. (2016) covered socioeconomic aspects related to autonomous vehicle adoption. Nordhoff et al. (2016) provided comprehensive literature on technology acceptance models. They proposed a conceptual model based on a holistic and comprehensive set of variables to predict the acceptance of driverless vehicles. Adnan et al. (2018) reviewed the previous literature on the impact of ethical implications associated with CAVs and their effect on CAV adoption. Faisal et al. (2019) reviewed existing literature on capability, planning, impact, and policy implications related to understanding CAVs, whereas Bagloee et al. (2016) covered a broad spectrum of implications associated with CAVs considering safety to machine ethics. Soteropoulos et al. (2019) provided the literature review on the impacts of CAV adoption on travel behavior and land use. Becker & Axhausen (2017) covered the surveys conducted to study the acceptance of CAVs. In contrast, Gkartzonikas & Gkritza (2019) also consider various choice studies and the stated preference surveys conducted to study CAV acceptance. Zmud et al. (2019) explored the research required to study behavioral responses towards CAVs. Shergold et al. (2016) provided the anticipated role of CAVs in providing mobility to older people. Clark et al. (2016) covered the existing literature available, understanding CAV adoption scenarios based on socioeconomic characteristics.

Studies available in the literature to investigate individuals' likelihood of adopting a CAV, installing autonomous technology in the existing vehicles or forecasting the market penetration rates of CAVs were selected. In the upcoming sections, a brief overview of all such studies is provided while segregating these into three categories: (i) aggregate methods (ii) disaggregate methods, and (iii) social influence.

2.1 Aggregate Methods

Aggregate methods consider an entire study area as a single homogeneous unit, hence following a top-down approach, and do not account for the heterogeneity of its various components and, therefore, fail to give descriptive results at a micro-level. Aggregate model results indicate the percentage of the total population at a certain time that has successfully adopted a new technology product depending upon the attributes of the innovation and characteristics of the population. Aggregate models fail to show the effect of change in the spatial distribution of transport infrastructure and socioeconomic characteristics in the future (El Zarwi et al., 2017). Aggregate models provide an insight into the overall behavior of the system considered (Schmittlein & Mahajan, 1982). The aggregate models date back to the 1960s when Bass (1969) developed a growth/diffusion model (referred to as the Bass model hereafter) based on the theory of diffusion and adoption given by Ryan and Gross (1943) and Rogers (1962).

Some studies used aggregate methods to quantify the market penetration of CAVs (Lavasani et al., 2016; Litman, 2014; Shabanpour, Shamshiripour, et al., 2018). Based on the adoption of innovative technologies in the past, Litman (2014) found that autonomous vehicles will cover

~50% of vehicle sales, ~40% of vehicle travel, and ~30% of the vehicle fleet by 2040. The author also considered optimistic and pessimistic scenarios. In both scenarios, in 2050, CAVs were likely to cover ~90% and ~75% of vehicle sales. Similarly, Lavasani et al. (2016) utilized a market penetration model based on the generalized Bass diffusion model (Schmittlein & Mahajan, 1982) and data available on market penetration of internet and hybrid electric vehicle sales to forecast the future sales of CAVs. The authors found that the adoption rate was directly proportional to the market size. In contrast, the initial cost of AVs did not affect the adoption rate. Results also enunciated that if CAVs are introduced in 2025, sales will cross 10 million units in 10 years, attaining a saturation in 35 years if the market size of 75% is assumed. Shabanpour, Shamshiripour, et al. (2018) utilized a Bass model (Bass, 1969) to forecast CAV market penetration of 71.25% by 2050.

2.2 Disaggregate methods

Unlike aggregate methods, disaggregate methods follow a bottom-up approach to capture the heterogeneity among every individual in the target population and, hence, progresses from one individual to the entire system. Disaggregate models usually include the formulation of probability or decision of an individual or a single household to adopt an innovation based on individual characteristics, alternatives and associated attributes, time (temporal description of diffusion), and communication channels. Disaggregate models are preferred over aggregate models because they consider heterogeneity in the decision process and are not limited to a particular geographical, cultural, or social area. Disaggregate models provide policy variables to optimize adaptors or resources (El Zarwi et al., 2017). Disaggregate models are also helpful to provide a unique framework for policy analysis (Schmittlein & Mahajan, 1982). Some of the disaggregate methods are based on the utility maximization principle, where an alternative with the highest utility or attractiveness is adopted.

Disaggregate methods, which have been employed to study the adoption of autonomous vehicles in various studies, include modified Bass model (Shabanpour, Shamshiripour, et al., 2018), discrete choice models (Bansal et al., 2016; Bansal & Kockelman, 2017; Berliner et al., 2019; El Zarwi et al., 2017; Haboucha et al., 2017; Howard & Dai, 2014; Jiang et al., 2019; Krueger et al., 2016; Lavieri et al., 2017; Malokin et al., 2015; Menon et al., 2015; Nair et al., 2018; Nazari et al., 2018; Nodjomian & Kockelman, 2019; Shabanpour et al., 2017; Shabanpour, Golshani, et al., 2018; Shin et al., 2015; Spurlock et al., 2019), agent-based models (D. Fagnant & Kockelman, 2014; Talebian & Mishra, 2018), structural equation models (Abraham et al., 2017; Asgari & Jin, 2019; Kaur & Rampersad, 2018; Leicht et al., 2018; Liu, Guo, et al., 2019; Liu, Yang, et al., 2019; Pettigrew et al., 2019) , and other miscellaneous types of models including correlation analysis, regression analysis and analysis of variance (Hohenberger et al., 2016; Kyriakidis et al., 2015; Liljamo et al., 2018; Nordhoff et al., 2018; Piao et al., 2016; Sanbonmatsu et al., 2018; Schoettle & Sivak, 2014b, 2014a; S. Wang & Zhao, 2019; Xu & Fan, 2019). We discuss all such studies in the upcoming subsections while covering the details about data, methodology, and key findings.

2.2.1 Choice models

Howard & Dai (2014) applied a logit model to 107 residents of California. Results showed that 46% of respondents favored autonomous vehicles for sharing the road space with normal traffic. The people of all income groups were concerned with the cost. Malokin et al. (2015) utilized a revealed preference survey of 2,120 commuters in the US in a multinomial logit (MNL) model.

Results showed the importance of productivity in CAVs as personalized and shared CAVs would see mode share changes of about 0.95% and 1.08% from public transit. Menon et al. (2015) used multivariate ordered logit on 1,156 respondents in the US to study their CAV adoption behavior. Results showed that benefits of increased productivity, less stressful driving, fewer crashes, and lower insurance prices positively affected consumer perceptions of CAV adoption. Shin et al. (2015) provided an analysis of preferences and willingness to pay (WTP) of 675 consumers in Korea towards adopting vehicles with advanced technologies using a multiple discrete-continuous probit (MCDP) model. Results indicated that older individuals were less likely to adopt vehicles with smart features whereas individuals who find such features useful were inclined to use such vehicles. Availability of smart vehicle features was related positively with vehicle choice, and low-income individuals were hesitant to adopt vehicles with smart vehicle technologies. Krueger et al. (2016) identified the preferences of 435 respondents in Australia towards shared CAVs with and without dynamic ride sharing (DRS) using a mixed logit model. The results showed that individuals who used shared mobility as passengers and drivers in the past are more likely to ride in shared CAVs with and without DRS, respectively.

Bansal & Kockelman (2017) used a simulated MNL model and survey results of 2,167 respondents in the US. The results showed that in the scenarios having at least a 10% WTP increment rate or 10% reduction in the price of technology, CAVs would be adopted by more than 90% of US residents in 2045. Daziano et al. (2017) used a mixed-mixed logit model on a survey of 1,260 Americans to study their WTP towards CAVs. The results showed that an average household would spend $3500 and $4900 for partial and full automation. El Zarwi et al. (2017) coalesced technology adoption models and latent class choice models (LCCM) to forecast the diffusion and adoption of new transportation services. The key results included that the male and high-income groups were more likely to be trendsetters. Haboucha et al. (2017) studied the preferences and attitudes of 731 respondents in Israel and the US towards CAVs using a mixed logit model. Results suggested that Israelis were more inclined towards autonomous vehicle adoption. Overall, 32% and 24% of respondents opted for personally owned and shared CAVs. Lavieri et al. (2017) modeled the adoption preferences of Americans towards owned and shared CAVs using a generalized heterogeneous data model (GHDM). Results indicated that tech-savvy, younger, and more educated individuals would be the early adaptors of CAVs. Shabanpour et al. (2017) used a mixed logit model while utilizing survey responses of 1,253 participants in the US to capture their preferences towards privately owned CAVs. Results showed that past experiences with accidents, more annual vehicle miles traveled, living far away from the workplace, people defining themselves as innovators, and favorable policies in terms of dedicated lanes were positively related to the adoption of privately owned CAVs.

Nazari et al. (2018) used a hybrid choice model to capture the interest of 2,726 survey respondents in the US in owning CAVs. Results indicated that males, young adults, self-employed, primary drivers in household vehicles, green travel patterns, and mobility-on-demand (MOD) savviness were positively related to owning a CAV. Nair et al. (2018) used a rank-ordered probit model to understand the interest levels of 1,365 survey respondents in the US towards different CAV-based travel modes. Results indicated that individuals who drive alone or carpool, multi-person households, and males were likely to own CAVs more than choosing other CAV-based travel modes i.e., ride sharing service with a backup driver, ride sharing service without a human backup driver, and carpooling. Shabanpour, Golshani, et al. (2018) added the best worst (BW) based approach to the MNL model to capture the CAV adoption behavior of 1,253 respondents in the US. Results showed that individuals with disabilities, higher income, and a high level of education were less sensitive to AVs' price and hence would be among the early adopters. Berliner et al. (2019) uncovered the perceptions of 2,261 early adopters of electric vehicles in California towards the CAVs using an ordered logit framework. Results indicated that males, larger households, those paying more for buying a new vehicle, those with increased knowledge about AV technology, and perceiving CAVs as safer than conventional vehicles were associated with increased likelihood of adopting a CAV. Jiang et al. (2019) explored behavior of 1,002 residents in Japan towards adopting CAVs using mixed logit model. Results indicated that individuals were more likely to adopt CAVs with lower purchase price, insurance and parking costs, and lower penetration rates. S. Wang & Zhao (2019) studied the impact of risk preferences associated with CAVs for 1,142 respondents in Singapore using mixed logit framework. Results indicated at disaggregate level, the elderly, females, poorer, and unemployed persons are more susceptible to risk, hence less likely to adopt a CAV. At the aggregate level, people misperceive risk probabilities, are risk-averse, and will underutilize CAV as compared to the optimal adoption rates under actual risk potential.

2.2.2 Structural equation models

Abraham et al. (2017) used structural equation modeling (SEM) on 2,954 respondents in the US to identify the factors affecting willingness to pay towards adopting a CAV. The results indicated younger adults were willing to pay more and had higher levels of trust and comfort in autonomous technology. Kaur & Rampersad (2018) used confirmatory factor analysis on 101 staff and students in the US. Results indicated the positive influence of reliability, performance expectancy, and trust on CAV adoption. Leicht et al. (2018) used SEM to analyze intention of 241 consumers in France towards purchasing a CAV. Results showed that effort expectancy, performance expectancy, and social influence were positively related to CAV adoption.

Asgari & Jin (2019) analyzed the perceptions of 1,198 Florida residents using SEM towards CAV adoption. Results indicated that individuals looking to minimize travel time and cost (mode-choice reasoning) and having trust issues with other passengers when using shared mobility were willing to pay more for CAV. Liu, Yang, et al. (2019) studied the acceptance behavior of 441 residents in China towards CAVs through SEM. Results indicated both direct and indirect effects of residents' social trust on their CAV acceptance. Among the indirect effects, perceived benefits and risks mediated the positive and negative impacts of social trust on CAV acceptance, respectively. Among the direct effects, social trust was positively related with WTP towards CAVs. Liu, Guo, et al. (2019) studied the willingness to pay towards CAV adoption of 1,355 respondents in China using SEM. Results indicated that approximately 34% of residents were willing to pay more than $2,900 extra to install autonomous technology in their next vehicle. Furthermore, about 40% of residents were willing to pay $0 to $2,900 extra for the autonomous technology. Pettigrew et al. (2019) applied latent profile analysis on survey responses of 1,345 respondents in Australia to capture their intention towards owning or sharing a CAV. Results indicated that first-movers/innovators (14% of the sample) were among the first buyers and most knowledgeable about CAVs, followed by likely adopters (17% of the sample) and AV ambivalent (19% of the sample).

2.2.3 Agent-based models

D. Fagnant & Kockelman (2014) utilized an agent-based model for the operation of shared CAVs in the US (Austin, TX). Results implied that in the base case, each CAV has the potential to replace about 12 privately owned vehicles. Talebian & Mishra (2018) coalesced diffusion of innovations with an agent-based modeling (ABM) framework to predict the long-term adoption of autonomous vehicles based on an institutional survey of 327 faculty and staff in the US. The results showed that full adoption would only be possible by 2050 if prices of CAVs decreased by 15 to 20% annually while a 5% reduction rate corresponded to 15% adoption of CAVs.

2.2.4 Other models

Schoettle and Sivak (Schoettle & Sivak, 2014b, 2014a) studied public opinion on CAVs in China, India, Japan, the USA, the UK, and Australia (approximately 500–600 respondents per country). The study's key findings were that the majority of the respondents had heard of automated vehicles before and had a generally favorable opinion, as well as high expectations about the benefits resulting from them. Kyriakidis et al. (2015) provided the perceptions of 5,000 individuals from 109 countries towards CAVs based on the correlation analysis of a short version of the big five personality traits (extraversion, agreeableness, openness to experience, conscientiousness, and neuroticism). Results showed a considerable variation between developed and developing countries over various questions. About 50% and 69% of respondents believed that autonomous vehicles will be in operation by 2030 and reach 50% market penetration by 2050, respectively. The appreciation and frequency of driving were positively related to adoption. Hohenberger et al. (2016) explored gender differences in willingness to adopt CAVs using a regression-based analysis on a sample of 1,603 respondents in Germany. Results indicate that males were more inclined to use CAVs than females because of the increased anxiety levels in females and increased pleasure levels in males when riding a CAV.

Liljamo et al. (2018) studied the attitudes of 2,036 respondents in Finland towards CAVs through cross-tabulation. The results showed that highly educated males living in densely populated areas and those not owning a vehicle had positive attitudes towards CAVs. Nordhoff et al. (2018) studied the acceptance of driverless vehicles for 7,775 respondents from 116 countries through principal component analysis (PCA). Results indicated that individuals perceive CAVs as convenient, easy to use, and joyful rides. Higher usefulness of CAVs (perceived), living in the city, and frequency of public transport was related positively to acceptance of CAVs. Trust, intention to use, and social influence were regarded as deciding factors for CAV acceptance. Shabanpour, Shamshiripour, et al. (2018) utilized a modified Bass model (Schmittlein & Mahajan, 1982) to capture the behavior of 1,253 respondents in the US towards CAV adoption. The results showed that individuals with certain sociodemographic characteristics like being married, highly educated, and wealthy are more likely to be among the first (innovators) to adopt CAVs. Furthermore, individuals making long-distance trips, paying high parking fees, and following a tech-savvy lifestyle are also likely to act as innovators to adopt AVs.

Sanbonmatsu et al. (2018) investigated 114 consumers' confidence and beliefs in CAVs through correlation analysis. Results indicate that consumers with the least information about CAVs and low trust in technology reflected negative views about CAVs. Spurlock et al. (2019) analyzed the adoption patterns for vehicle automation for 1,045 Americans using linear probability model ordinal least squares regression. Results showed that younger residents, those with high household income, those who desire a travel mode minimizing environmental impact, and males were related positively with interest in adopting automated technologies. Xu & Fan (2019) investigated the risk perceptions associated with CAVs in China for 1,164 respondents through one-way ANOVA analysis. Results showed that majority of respondents were aware of AV technology and had a positive impression of CAVs and believed that CAVs will reduce risk and provide lower insurance rates.

2.3 Social influence

In addition to aggregate and disaggregate approaches, a handful of studies capture the impact of information received from their peers in the social network on individuals' decision to adopt CAVs (Acheampong et al., 2021; Acheampong & Cugurullo, 2019; Jing et al., 2019; Leicht et al., 2018; Nordhoff et al., 2018; Panagiotopoulos & Dimitrakopoulos, 2018; Rahman et al., 2019). Leicht et al. (2018) found the positive impact of social status and social influence on CAV adoption,consistent with Nordhoff et al. (2018) and Panagiotopoulos & Dimitrakopoulos (2018). Acheampong (Acheampong et al., 2021; Acheampong & Cugurullo, 2019) found similar results for the impact of social status on intention to use CAVs, whereas Jing et al. (2019) showed the positive impact of social influence. Rahman et al. (2019) found the positive effect of social influence in older adults on their acceptance of CAVs. However, all these studies did not consider the social network or communication frequency among the peers while deciding to adopt a CAV. It is worth mentioning that when peer to peer interaction over social network is considered in combination with other information obtained from media, social media and blogs, the phenomenon is collectively referred to as word-of-mouth (WOM) and prolific studies exist on capturing the impact of WOM on acceptance of a novel product (Gupta & Harris, 2010; Ha, 2002; Huete-Alcocer, 2017). However, literature is limited in capturing the impact of WOM on the CAV acceptance (Talebian & Mishra, 2018).

From the literature covered in this section, it is evident that no studies exist in capturing the CAV adoption preferences of individuals based on their social network or WOM. A handful of studies provide the future forecasts for CAVs (Bansal & Kockelman, 2017; Lavasani et al., 2016; Litman, 2014; Shabanpour, Shamshiripour, et al., 2018) but do not consider the impact of peer-to-peer interaction and information received from the media. In addition, no studies exist to capture the CAV adoption preferences for an entire statewide population. Hence, in this project, we utilize the fusion of hybrid choice modeling with agent-based modeling based on statewide survey results capturing the social network-related information and the intention to use CAVs.

Chapter 3 Data

As part of the analysis, we conducted a survey in Tennessee to capture the residents' intention towards adopting CAVs. This section describes the survey design and methodology followed by the survey data collection and the analysis of the survey results. This section also includes the descriptive statistics of the final survey data used in the modeling framework.

3.1 Survey design and methodology

Almost all scientific research is based on data as it enabled scientists and researchers to test various theories and hypotheses. Data is utilized to develop models to predict the future behavior of a specific phenomenon, calibrate the models to capture the recent updates in the phenomenon or validate the developed models to measure their precision and accuracy. Some areas of scientific research can be carried out based on the data obtained from laboratory research; however, not all the scientific areas can obtain the data from the laboratory experiments, especially transportation, and, hence, real-world data or observation becomes a necessary and principal component for such research areas. Such real data can be recorded using stated preference (SP) or revealed preference (RP) surveys. As per Kroes & Sheldon (1988), SP methods can be defined as "a family of techniques which use statements of individual respondents about their preferences" for a set of choices to calculate utility functions. As compared to SP, RP methods represent the actual behavior, and the word reveal makes it obvious that they include the real decisions made by individuals from a set of existing alternatives. In other words, SP surveys include hypothetical alternatives (ex-ante information). In contrast, RP surveys include existing alternatives (ex-post information).

The main aim of this project is to forecast the CAV acceptance in Tennessee. However, CAVs are not available in the market yet, at least not for the general public. Therefore, to capture the objective and obtain the individuals' preferences towards CAVs, a statewide SP survey was conducted. The survey process included three interdependent elements:

1. Sampling methodology
2. Survey methodology
3. Survey instrument

3.1.1 Sampling Methodology

The sampling methodology includes a tradeoff between survey quantity and survey quality based on selected sample size constrained on the available budget. An increase in sample size decreases the variance but increases cost and vice versa. Therefore, an optimal design is required, and, in this section, this research will try to answer, "*How many Tennessee residents are required to participate in the survey?*". The optimal sample size should be enough to estimate results for the whole population with an acceptable level of precision and confidence.

Generally, in literature, sampling methodologies are divided into three major categories: random sampling methods, quasi-random, and non- random. this project used a random sampling method, where each population unit has an equal probability of being chosen. In addition, a random sample is unbiased and simple when compared to other two methodologies (Stopher, 2012). We utilized population estimates from the 2018 American Community Survey

(ACS) for sample size calculations. The desired confidence level, precision required, and degree of variability are required to determine enough sample size. Precision, also known as sampling error, is the tolerance or permissible limit of accepting error, i.e., the difference between a population value and estimated value. The confidence level implies the certainty of an acceptable precision level.

In contrast, the degree of variability represents heterogeneity in the population. The greater the heterogeneity, the larger the sample size is required. In past literature, Cochran's formula is the most common approach to estimate sample size. As per Cochran (1977), the optimal sample size for an infinite population can be calculated as:

$$n^* = \frac{z^2pq}{e^2}$$

$$where, n^* = sample\ size, z = critical\ value\ for\ desired\ confidence\ level,$$
$$e = desired\ level\ of\ precision,$$
$$p = degree\ of\ variability\ (estimated\ proportion\ of\ an\ attirbute\ present\ in\ the\ population)$$
$$q = 1 - p$$

When the population is known or finite, then Cochran (1977) proposed a correction formula to reduce the calculated sample size further:

$$n = \frac{n^*}{1 + \frac{(n^* - 1)}{N}}$$

$$where, N = population\ size,$$

$$n = sample\ size\ corrected\ for\ finite\ population$$

Utilizing the population data from ACS 2018, sample sizes using Cochran's formula for finite population, under different desired levels of confidence level and precision, are presented in Table 3.1. Assuming the standard value of 95% confidence level and ±2% level of precision, a sample size of 4,600 respondents was targeted for the survey. A 99% confidence level was not selected because of significantly higher sample size resulting in increased difficulty of getting responses from all demographical groups.

3.1.2 Survey Methodology

Since the project's main objective is to capture the perceptions and views of Tennessee residents, this research designed the survey framework based on the existing literature (Talebian & Mishra, 2018). The final survey questionnaire (included in Appendix C) included eight different blocks with a total of 46 questions.

The first block of the survey questionnaire included the consent paragraph. Participants were provided preliminary information about the survey, data confidentiality, and incentives. The first block also included screening questions to check whether the participant agreed to the consent, was more than 18 years of age, and living in Tennessee. The participants were asked about their age (to screen out respondents aged less than 18 years) and 5-digit ZIP code of their home location. Only the participants satisfying these criteria filled out the survey.

The second block included questions about participants' socioeconomic characteristics like gender, ethnicity, marital status, educational qualification, and annual income. The third block included questions about the respondents' tech-savvy lifestyles and covered the frequency of using TV, radio, smartphone, and smart home appliances. The fourth block included household and vehicle ownership characteristics such as household size, household location, annual household income, number of vehicles in the household, and vehicle purchasing behavior.

Table 3.1

Sample size under different desired confidence levels and precision: Cochran Formula

Precision Level	Confidence Level	Sample size
0.01	**90%**	6,717
	95%	9,590
	99%	16,599
0.02	**90%**	3,219
	95%	4,596
	99%	7,960
0.03	**90%**	747
	95%	1,067
	99%	1,848
0.04	**90%**	420
	95%	600
	99%	1,040

The fifth block introduced the questions about work and travel-related activities in the form of frequency of working from home, disability limiting driving abilities, past vehicle crashes, annual vehicle mileage, and different travel modes for daily travel. The sixth block included the questions about CAVs, and the term "Autonomous car" was used to refer to CAVs. The questions covered respondent's familiarity with CAVs and willingness to pay to buy and maintain a CAV. The sixth block also introduced the social network concept while asking questions about the work social ties developed and their impact on vehicle purchasing decisions.

The seventh block captured respondent's attitudes and perceptions towards benefits and concerns of CAVs. Before presenting the questions, the driving operation of CAVs was explained as: *"An autonomous car is a vehicle that is capable of sensing its environment and navigating without human input. No driver attention is required for safety, i.e., the driver may safely go to sleep or leave the driver's seat. Autonomous operation is only supported under certain circumstances and areas. Outside of these areas or circumstances, the car will be able to safely abort the trip, i.e., park the car, if the driver does not retake control."*

Finally, the eighth and last block asked the importance of choosing a different mode of transport, including a personally owned CAV, shared CAV, and autonomous transit bus services. At the end, respondents were asked about their intention to enter a lottery to win a gift card for completing the survey.

3.1.3 Survey Instrument

The survey was distributed completely online on different platforms and mediums. Depending on the platform, randomly selected Tennessee residents were invited to participate in the survey after sharing an anonymous link. If a recipient chose to participate in the survey, he/she needed to click on the link provided in the respective post. The link would take the respondent to a survey hosted in Qualtrics. The survey had a welcome page that provided an overview of the survey and asked for the participants' consent. The survey also offered a $10 Amazon gift card to 50 participants selected at random to encourage participation. To be eligible to enter the raffle, the respondent was asked to enter his/her email only if the respondent chose to enter at the end of the survey. The respondent was free to stop responding to questions at any point of time he/she wanted to. We posted and distributed the survey on the following platforms:

a) **Social media and emails:** Location-centered (only in Tennessee) advertisements of the survey were posted on Facebook and Instagram. The survey link was also distributed to different educational institutes in Tennessee through emails.
b) **Amazon Mechanical Turk (MTurk):** Amazon MTurk is a crowdsourcing platform where the users are paid to complete human-related tasks. The survey was sent out as a human task to the existing MTurk userbase living in Tennessee. Users who opted to complete the survey were given an incentive. To complete the survey, the respondents were offered an incentive of $0.50 to $1.50, depending upon the response rate, in addition to the chance of winning the Amazon gift card. At the end of the survey in Qualtrics, the respondents were provided a unique random five-digit code, which they needed to enter in Amazon MTurk. The Amazon MTurk incentive was only distributed after the respondent entered the correct five-digit code. In MTurk, for collecting quality responses, the survey was displayed as a human intelligence task (HIT) to workers. Two additional constraints were set in Amazon Turk i.e., the minimum number of approved HITs as 100 and a HIT approval rate of at least 95%.

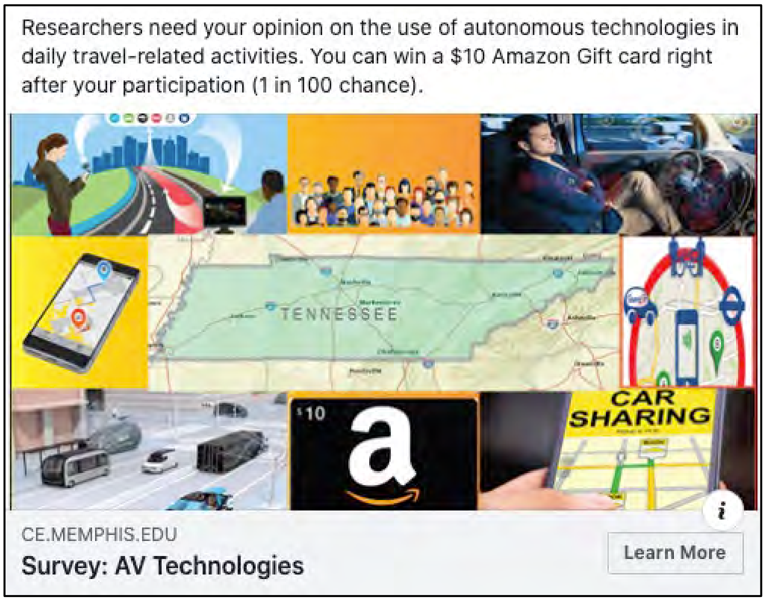


Figure 3.1
Sample advertisement displayed to Tennessee residents on Facebook

c) **Dynata:** The data analytics company "Dynata" collected 3,000+ responses from Tennessee residents. A marginal fee was paid per response to Dynata.

3.2 Survey data collection and analysis

The Division of Research and Sponsored Programs at the University of Memphis processed the survey. Institutional Review Board (IRB) approved it in an expedited track. The survey was administered entirely online and was distributed to the residents of Tennessee through three different channels: (i) Amazon Mechanical Turk (MTurk), (ii) Social media (Facebook and Instagram), and higher education institutes in the state of Tennessee (iii) Panel from Dynata: a data analytics company. This section discusses the number of responses obtained from different distribution channels, county distribution of the responses and key results, and descriptive statistics of the final survey dataset.

3.2.1 Survey web-dashboard

To present the survey results to a larger audience, a survey dashboard was also developed using “flexdashboard” and “shiny” packages in R (Chang et al., 2015; Rimal, 2021). The dashboard includes a brief introduction to the survey methodology, visualization of the survey results, and interactive maps demonstrating the modeling results. The survey dashboard can be accessed from this link to explore survey results interactively. Figure 3.2 presents a snapshot of the homepage of the survey dashboard.

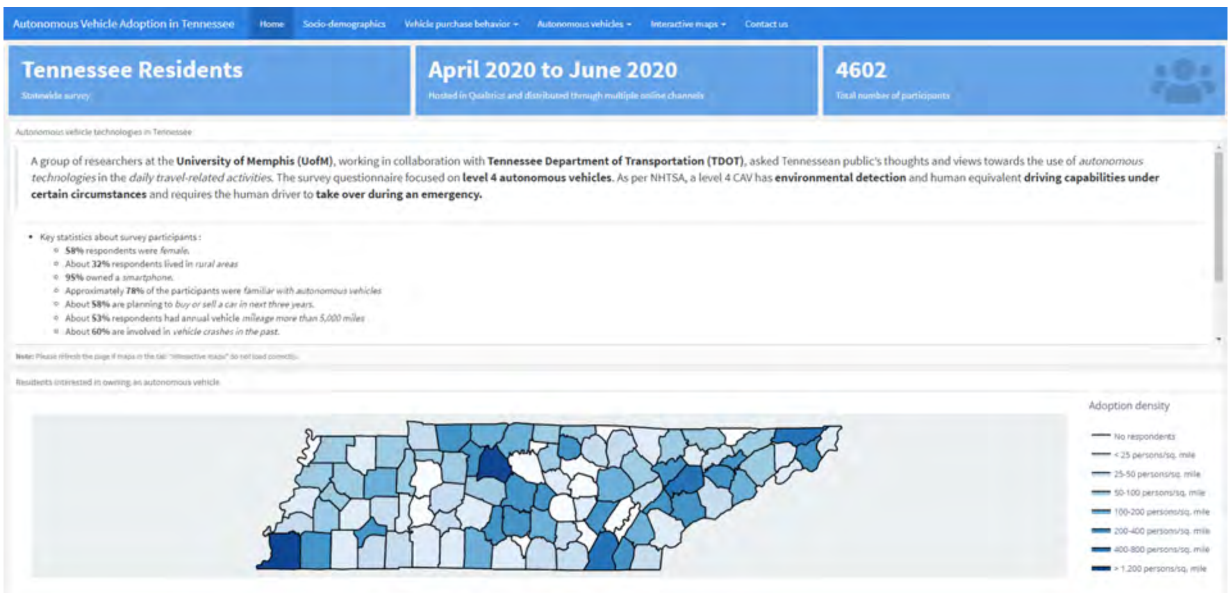


Figure 3.2

A snapshot of the welcome page of the survey web-dashboard

3.2.2 Number of survey participants

The responses were collected from March 2020 to May 2020. 988 responses were received from MTurk, and after removing incomplete responses, the number reduced to 886. 526 responses were collected from social media and educational institutes, and after filtering out the incompletes, responses were reduced to 413.

4,132 responses were collected from the hired panel of Dynata, and after removing the incompletes, the total responses were reduced to 3,303. After combining all the responses from all channels, the final sample includes 4,602 responses that satisfied the 4,596 sample size requirement. In the dataset, about 2,511 cells were missing from a total of 317,558 cells (4,602 rows and 69 columns) with a missing rate of 0.0079. A multivariate normal imputation was performed using the R package "Amelia" (Honaker et al., 2011) to fill these cells. The average response time to complete the survey was approximately 10 minutes.

Figure 3.3 shows the county distribution of survey participants (based on zip codes). Responses were received from 81 counties (a total of 95 counties). The counties with few or no responses house rural populations. The majority of the responses were from the counties including four major cities of Tennessee, i.e., Chattanooga, Knoxville, Memphis, and Nashville. Table 3.2 delineates the comparison of survey demographics within the population of Tennessee as per ACS 2018 (Manson et al., 2019). The survey sample overrepresented younger and female residents. Overall, the difference was at most 8% in all strata of age, gender, and ethnicity.

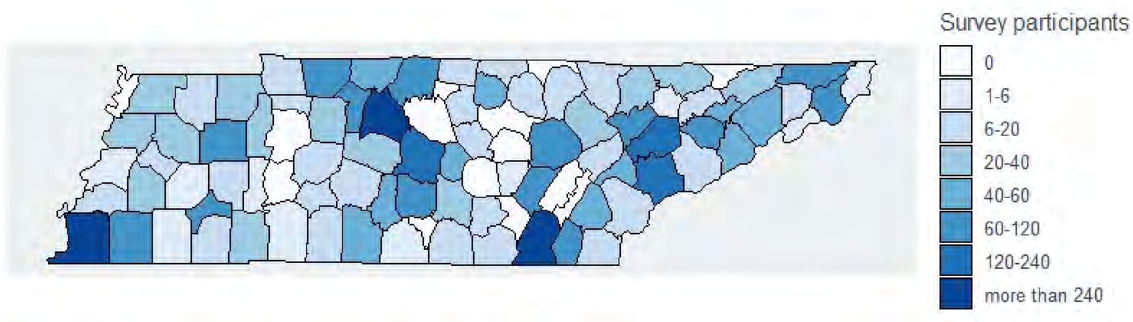


Figure 3.1
County wise distribution of survey participants (n= 4,602)

Table 3.1
Comparison of survey demographics (Sample Size 4,602 people) with the population of Tennessee (6,597,381 people).

Descriptor	Socioeconomic characteristic	Tennessee	Sample	Difference
Gender	Male	48.80%	42.44%	6.36%
	Female	51.20%	57.56%	-6.36%
Age	18 to 24 years	6.90%	14.19%	-7.29%
	25 to 34 years	13.30%	21.36%	-8.06%
	35 to 44 years	12.70%	17.23%	-4.53%
	45 to 54 years	13.60%	13.43%	0.17%
	55 to 59 years	6.80%	10.13%	-3.33%
	60 to 64 years	6.20%	8.69%	-2.49%
	65 to 74 years	9.20%	12.21%	-3.01%
	75 years and over	6.20%	2.76%	3.44%
Race	White	74.26%	77.25%	-2.99%
	Black or African American	16.66%	14.84%	1.82%
	American Indian and Alaska Native	0.23%	0.87%	-0.64%
	Asian	1.66%	2.28%	-0.62%
	Native Hawaiian and Pacific Islander	0.05%	0.24%	-0.19%
	Some other race	5.28%	2.78%	2.50%
	Two or more races	1.86%	1.74%	0.12%

3.2.3 Survey results

This section presents the results of the survey responses received from all distribution channels. Figure 3.4 below portrays the selected demographics of the sample. In terms of age, approximately 58% of respondents were female. The majority of respondents were aged between 25 to 34 years, followed by 35-44 years. Whites were in the majority with a proportion of 77%, and most respondents had an income of $100,000 or more. The majority of respondents graduated from college and were married.

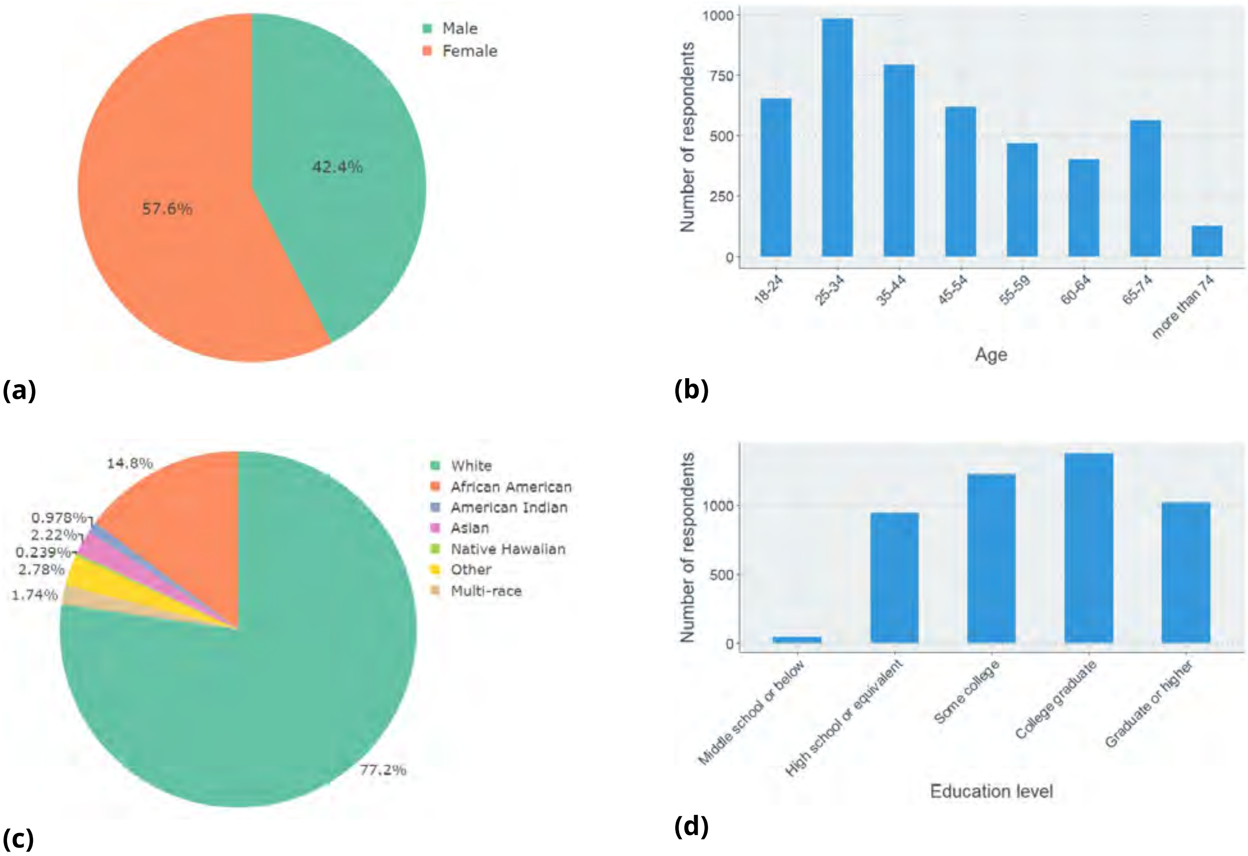


Figure 3.4

Demographics (N=4,602) (a) Gender (b) Age (c) Ethnicity (d) Education attainment (e) Personal annual income and (f) Marital status.

Figure 3.5 presents the respondents' interest in different characteristics of CAVs. Overall, respondents were interested in price, quality, environmental friendliness, and vehicle's ability to eliminate multiple trips to the service station. The respondents were not interested in improving their personal image through CAVs which can be attributed to the emerging stage of autonomous technology.

Figure 3.6 portrays respondents' trust in different information channels. Respondents preferred personal research and peers over car dealers and media advertisements. Figure 3.7 displays the importance of input from the peer network (both work and non-work) on respondents' decision to purchase a CAV. Overall, the respondents consider these inputs necessary. Figure 3.8 demonstrates the impact of purchasing a CAV on the social network of the respondents. Respondents had mixed feelings about losing friends after buying a CAV. In contrast, respondents did not think that buying a CAV would improve their social status. Figure 3.9 shows the frequency of using different tech-based services. Respondents reported watching TV and listening to the radio more frequently than using smartphones to control smart home devices and GPS navigation.

Figure 3.10 presents the vehicle purchasing characteristics of the respondents. Almost 60% of respondents had plans to buy a vehicle in the next three years. The majority of respondents were willing to pay between $5,000 and $10,000 for a regular car. Also, about 80% of respondents were familiar with CAVs. The majority were not willing to pay not more than $5,000 in addition to the price of a regular car for buying a CAV. Figure 3.11 and Figure 3.12 present perceptions of respondents towards negative and positive impacts of CAVs. The overall majority of respondents were concerned about the barriers and interested in the benefits of CAVs. Figure 3.13 portrays the experience with different travel modes. Most respondents used private cars for their daily commute.

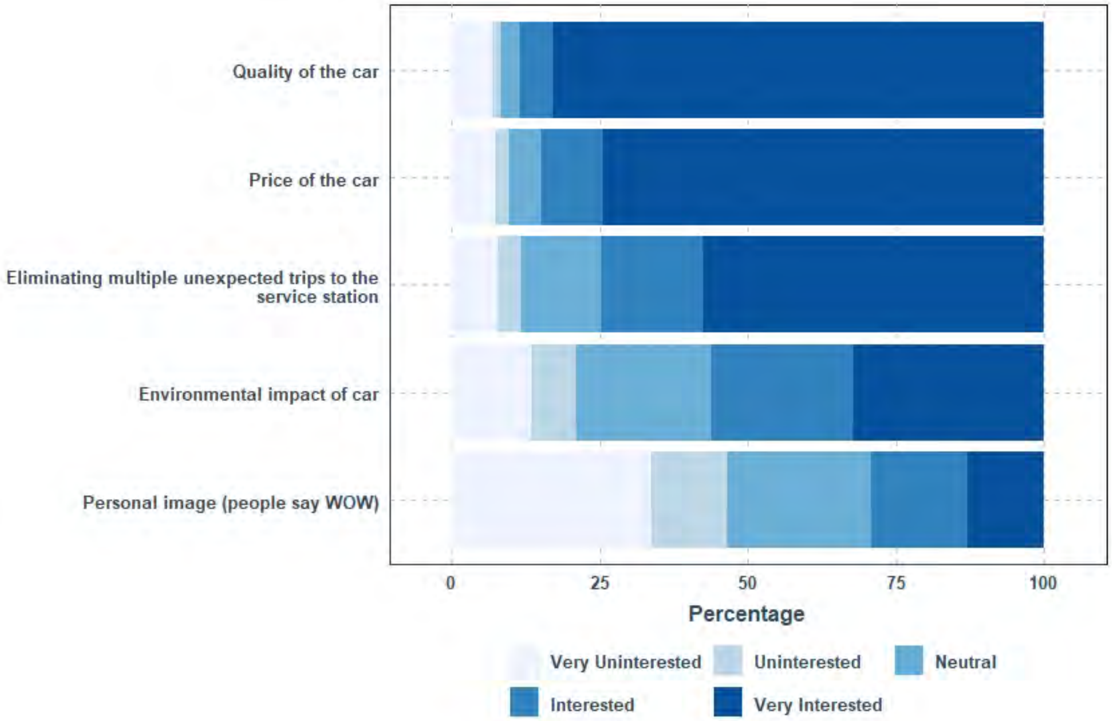


Figure 3.5
Respondents' interest in different vehicle-related impacts (N= 4,602)

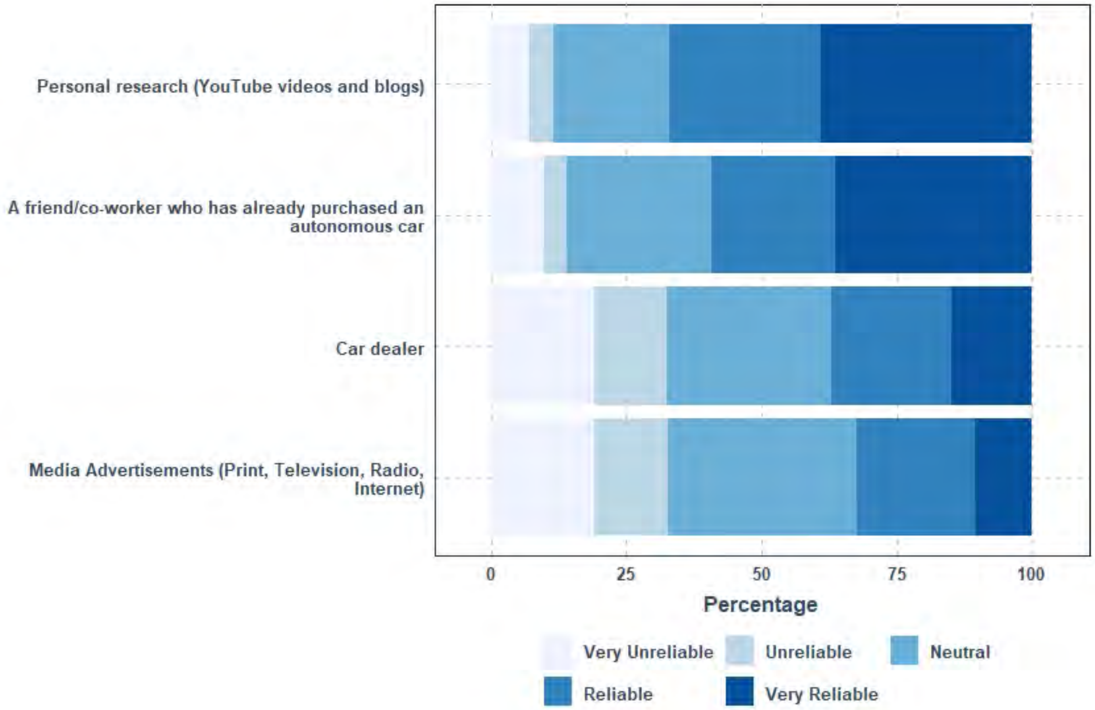


Figure 3.6

Respondents' reliability on different sources of information about CAVs (N= 4,602)

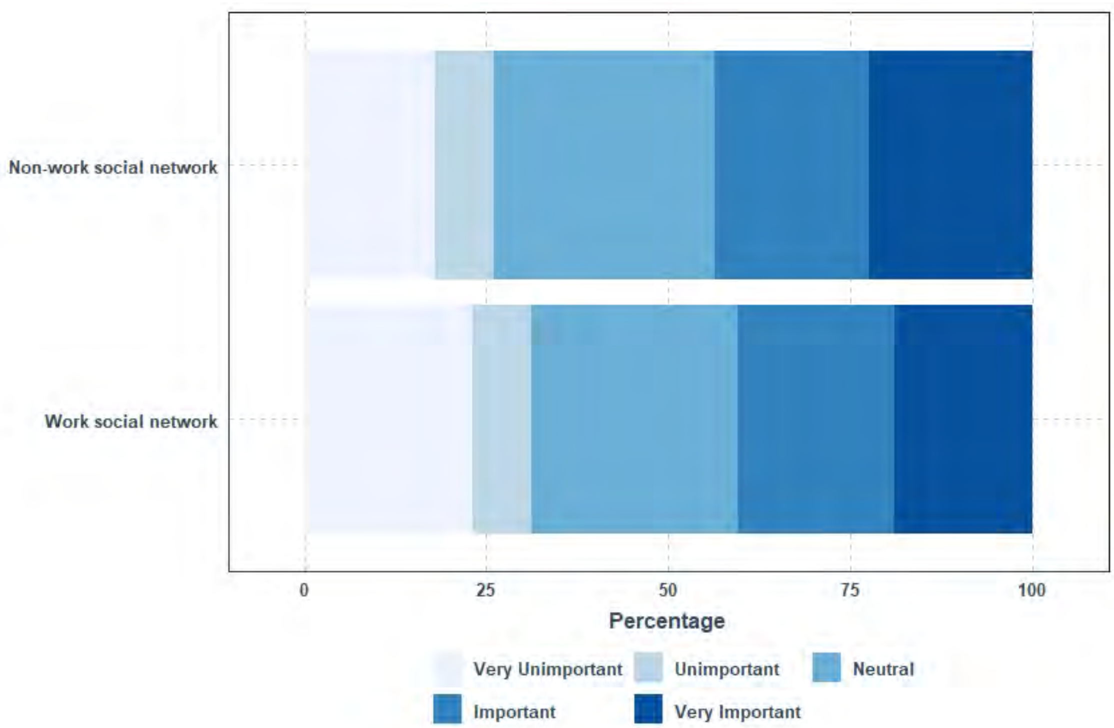


Figure 3.7

Respondents' importance towards input about CAVs from their peers (N= 4,602)

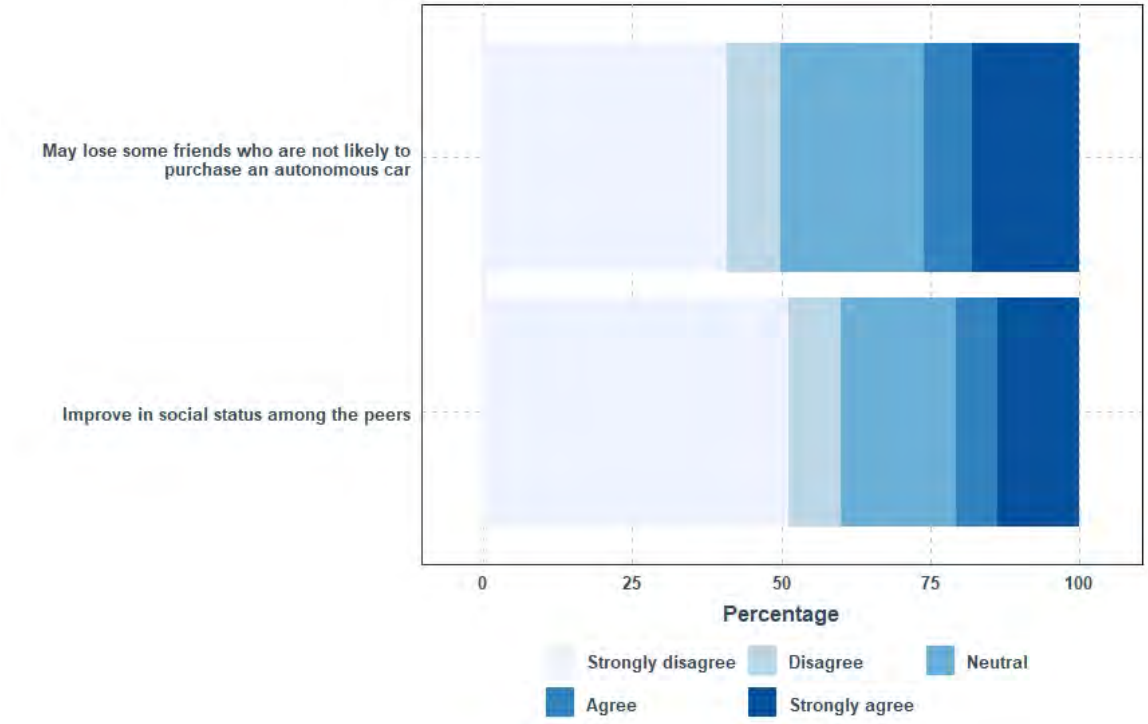


Figure 3.8

Respondents' perception towards their peer network if they choose to purchase a CAV (N= 4,602).

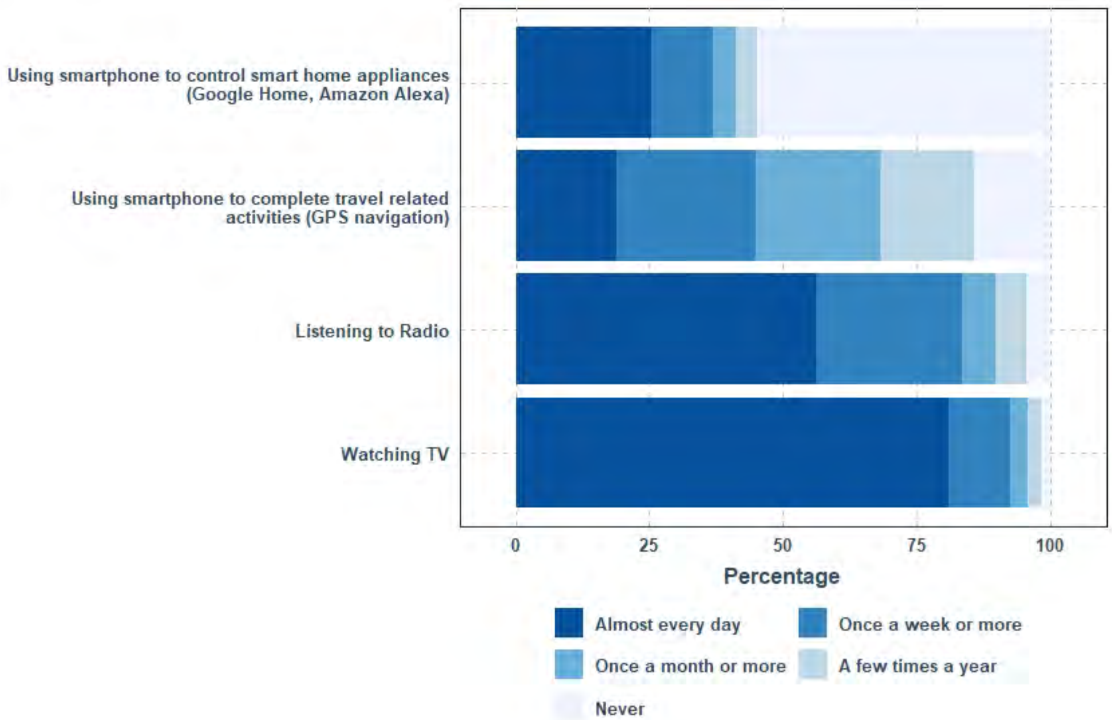


Figure 3.9

Respondents' frequency of using different tech-based services (N= 4,602)

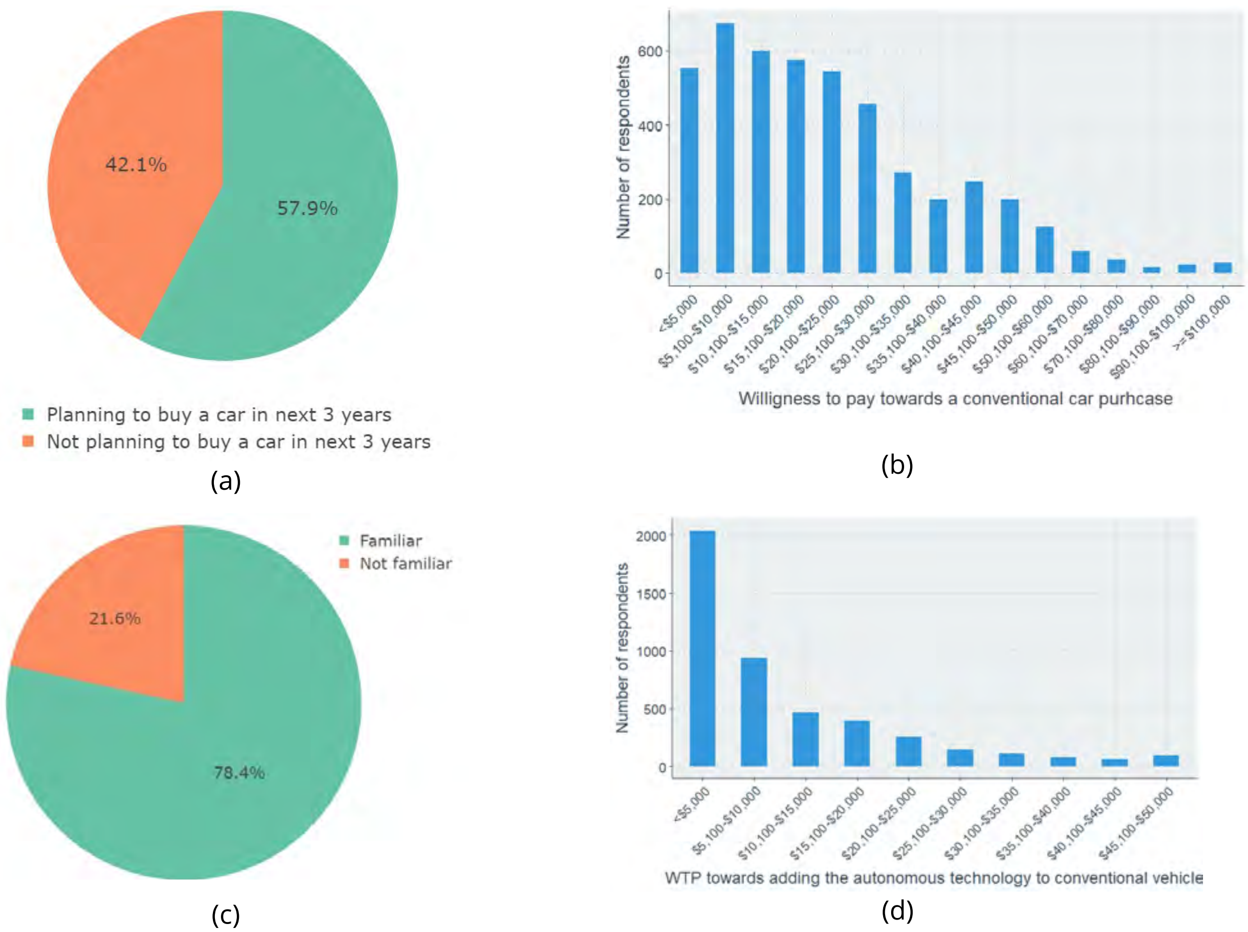


Figure 3.10

Vehicle purchasing characteristics (N= 4,602) (a) Plans to buy a vehicle in next 3 years (b) WTP for a regular car (c) Familiarity with CAVs and (d) WTP additional for autonomous technology

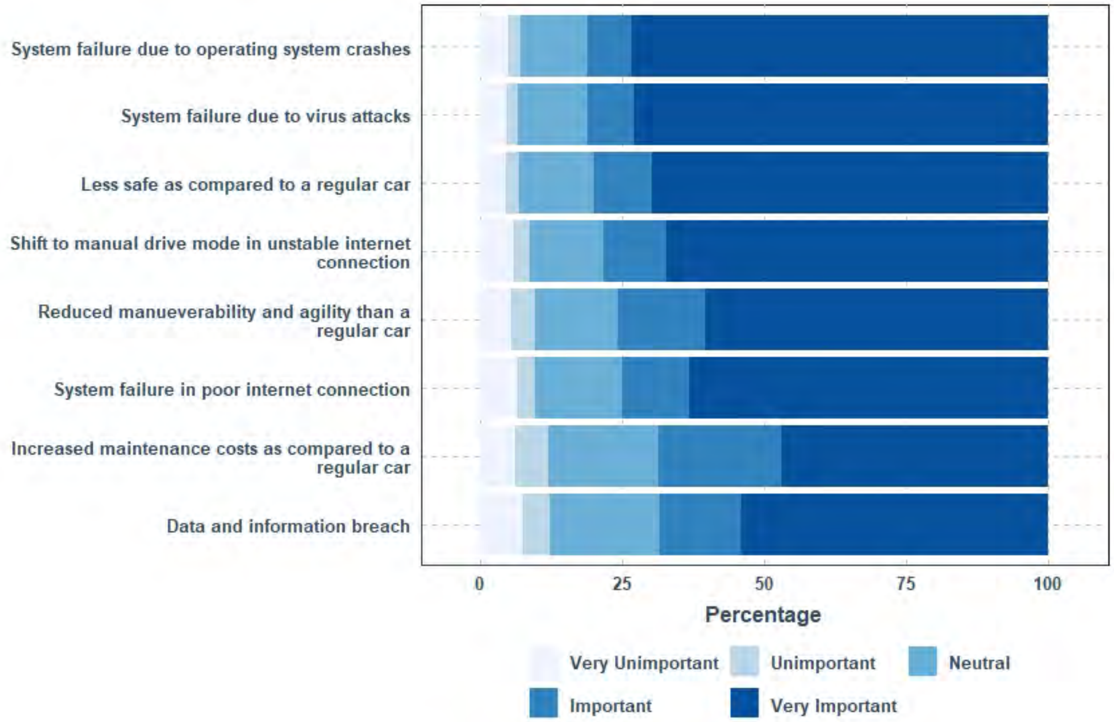


Figure 3.11

Respondents' perception towards negative impacts of CAVs (N=4,602)

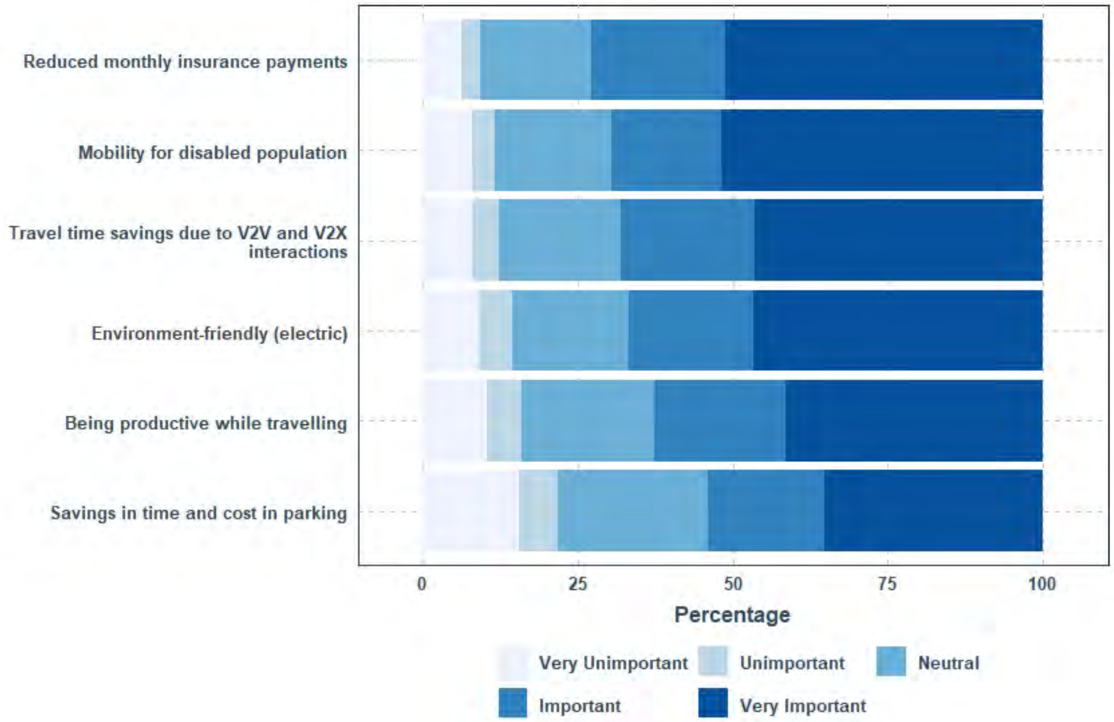


Figure 3.12

Respondents' perception towards positive impacts of CAVs (N=4,602)

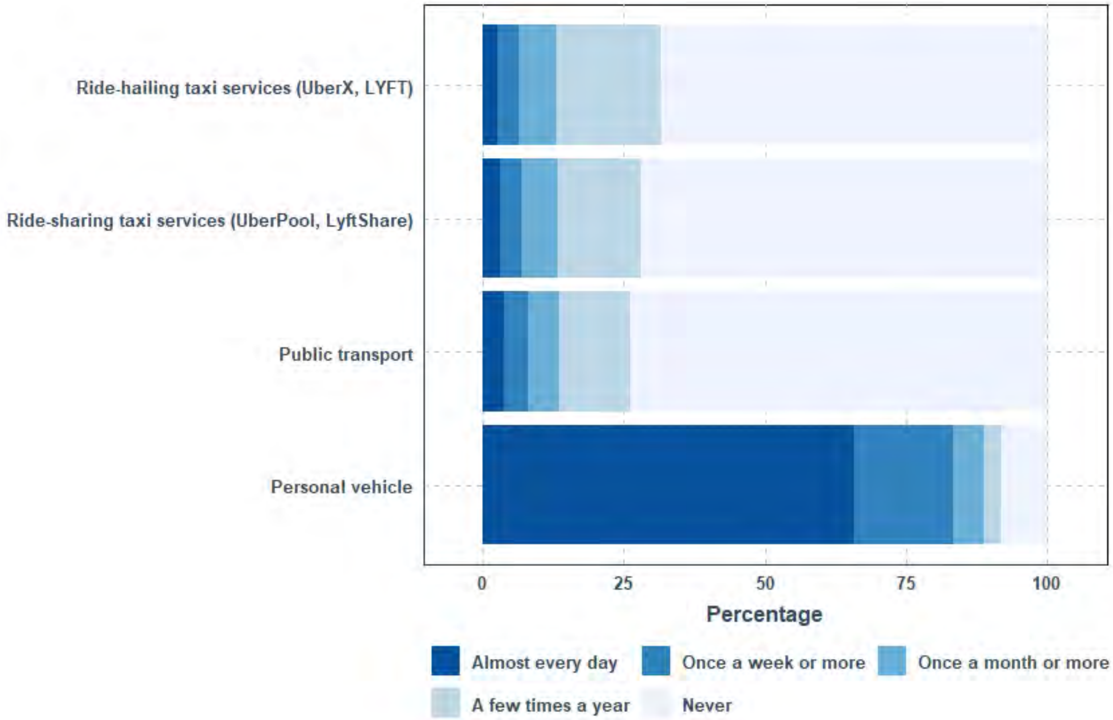


Figure 3.13
Respondents' experience with different travel modes (N=4,602)

3.2.4 Intention to use/adopt CAV-based travel modes

The original question in the survey to capture the respondents' interest towards five different CAV-based travel modes had seven levels of the Likert scale (Very Uninterested to Very Interested). However, for modeling purposes, the question was transformed into three levels i.e., "Very uninterested, Uninterested, Somewhat Uninterested, and Neutral" to "Not Interested or Reject"; "Interested, Somewhat Interested" to "Interested or Will Adopt"; "Very interested" to "Very Interested or Adopt." Figure 3.14 demonstrates the respondents' intention to use different CAV-based travel modes. The majority of respondents were inclined to own a CAV, followed by ride-hailing CAV services with a backup driver present.

3.2.5 Descriptive statistics

This section presents the descriptive statistics of the entire dataset utilized in the modeling section. Table 3.3 and Table 3.4 delineate the descriptive statistics of categorical and continuous attributes in the survey dataset, respectively. The majority of respondents never worked from home, had a flexible work schedule, had annual vehicle mileage over 5,000 miles, purchased a car every five to ten years, were willing to pay more if CAVs drive themselves to a service station, were not willing to pay anything (annually) to maintain a CAV, owned a smartphone, had been involved in vehicle crashes, frequently communicated with peers, and own two cars in their household. On average, respondents have 22 peers in their social network. Being consistent with the existing literature implying the requirement assigning two-thirds of the data for model training (Raschka, 2018) for cross-validation purposes, the dataset was split as 70:30 for the train and test dataset.

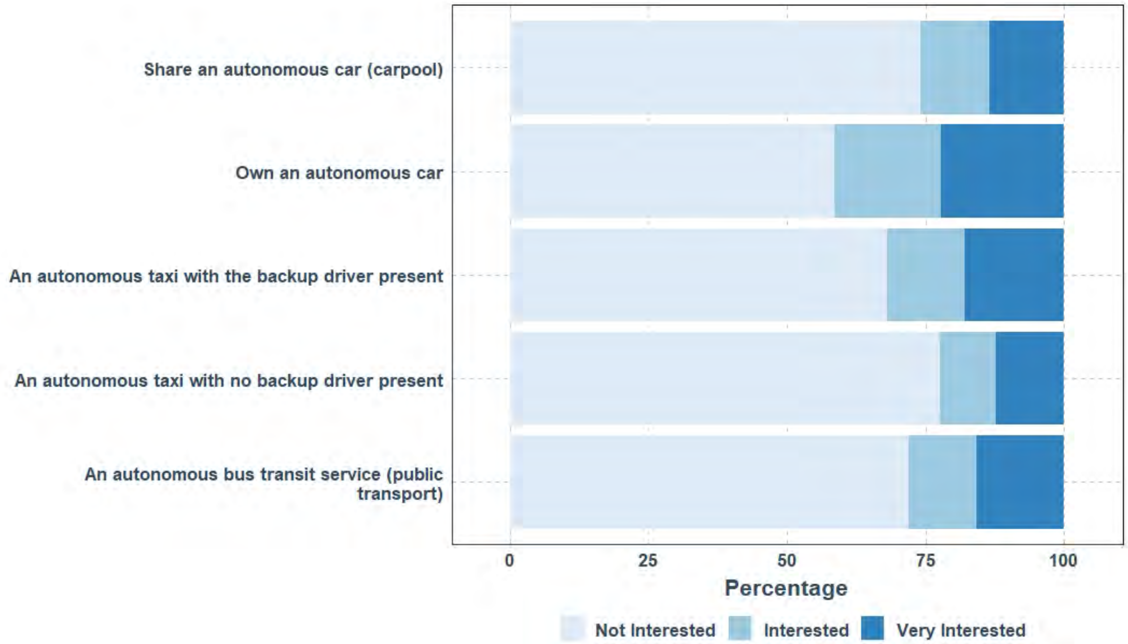


Figure 3.14
Respondents' intention to use different CAV-based travel modes (N=4,602)

Table 3.3
Descriptive statistics of categorical attributes in the dataset (N= 4,602)

Attribute	Description	Percentage
Gender	Male	42%
	Female	58%
Age	Less than 35	36%
	35 to 54	30%
	more than 54	34%
Ethnicity	White	77%
	African American	15%
	Others	8%
Educational Attainment	High school or below	22%
	Some College	26%
	College Graduate	30%
	Master's, doctoral or professional degree	22%
Marital status	Single	29%
	Married	57%
	Separated, divorced, widowed	14%
Approximate annual income	less than $35,000	37%
	$35,000-$75,000	34%
	more than $75,000	29%
Frequency of working from home	Frequent (everyday)	42%
	Infrequent (once a week to a year)	13%
	Never	45%
Flexibility in work schedule	Flexible	45%
	Somewhat flexible	25%
	Inflexible	30%
Disability limiting driving ability	Yes	14%
	No	86%
Household location	Urban	28%
	Semi-urban	40%
	Rural	32%
Household members	Two or less	55%
	Three or more	45%
Approximate annual household income	less than $35,000	30%
	$35,000-$100,000	47%
	more than $100,000	23%
Number of cars in the household	Zero and one	38%
	Two	40%
	Three or more	22%
Annual vehicle mileage	less than 5,000 miles	47%
	More than 5,000 miles	53%
Frequency of purchasing a car (household)	Frequently (once a year to every 2-3 years)	23%
	Moderate (once every 5 to 10 years)	65%
	Infrequent (once every 15 to 20 years)	12%

Attribute	Description	Percentage
New cars purchased in last 10 years in the household	Zero and one	37%
	Two	32%
	Three or more	31%
Used cars purchased in last 10 years in the household	Zero	32%
	One	28%
	Two or more	39%
Any plans to buy or sell a car in next three years	Yes	58%
	No	42%
Willing to pay more if CAV drive themselves to service stations	Yes	40%
	No	60%
Willingness to pay towards buying a regular car	less than $15,000	40%
	$15,000-$30,000	34%
	more than $30,000	26%
Willingness to pay more towards buying a CAV than regular car	less than $2,500	44%
	$2,500-$10,000	31%
	more than $10,000	25%
Willingness to pay more towards maintaining a CAV than regular car (annually)	$0	40%
	$0-$300	29%
	more than $300	31%
Frequency of listening to Radio	Frequent (everyday)	57%
	Infrequent (once a week to a year)	39%
	Never	4%
Frequency of watching TV	Frequent (everyday)	81%
	Infrequent (once a week to a year)	17%
	Never	2%
Frequency of using smart home appliances like Amazon Alexa	Frequent (everyday)	25%
	Infrequent (once a week to a year)	20%
	Never	55%
Frequency of using GPS Navigation	Frequent (everyday)	19%
	Infrequent (once a week to a year)	67%
	Never	14%
Own a Smartphone	Yes	95%
	No	5%
Number of peers having knowledge about cars	Zero	28%
	one to two peers	30%
	more than two peers	42%
Past involvement in vehicle crash(s)	Yes	60%
	No	40%
Frequency of communication with social ties developed at work	Frequent (2-3 times a week to daily)	55%
	Sometimes (every couple of weeks to month)	21%
	Infrequent (once per month to every few months)	24%
	Frequent (everyday)	84%

Attribute	Description	Percentage
Frequency of using private car for daily commute	Infrequent (once a week to a year)	5%
	Never	11%
Familiarity with CAVs	Yes	78%
	No	22%
Frequency of using public transport for daily commute	Frequent (everyday)	8%
	Infrequent (once a week to a year)	5%
	Never	87%
Frequency of using ride sharing services for daily commute	Frequent (everyday)	7%
	Infrequent (once a week to a year)	7%
	Never	86%
Frequency of using ride hailing services for daily commute	Frequent (everyday)	6%
	Infrequent (once a week to a year)	7%
	Never	87%

Table 3.4
Descriptive statistics of continuous and Likert scale-based attributes in the dataset (N= 4,602)

Attribute notation if applicable	Description	Statistics (min, mean, std. dev. and max)
-	Number of social ties in social network	min = 0, **μ**= 22.17, **σ**= 27.72, max = 100
ATT01: CarPrice	Importance of price of car in purchasing decision	min = 1, **μ**= 5.88, **σ**= 1.65, max = 7
ATT02: CarQuality	Importance of car quality in purchasing decision	min = 1, **μ**= 6.11, **σ**= 1.59, max = 7
ATT03: Environment	Importance of environmental impact in purchasing decision	min = 1, **μ**= 4.58, **σ**= 1.68, max = 7
ATT04: PersonalImage	Importance to personal image while purchasing a car	min = 1, **μ**= 3.49, **σ**= 1.75, max = 7
ATT05: ServiceStationTrips	Importance of car's ability to eliminate multiple unexpected trips to the service station while purchasing a car	min = 1, **μ**= 5.38, **σ**= 1.66, max = 7
ATT06: FriendRel	Reliable source of information: A friend/co-worker who has already purchased a self-driving car	min = 1, **μ**= 4.77, **σ**= 1.58, max = 7
ATT07: AdvtRel	Reliable source of information: Media Advertisements (Print, Television, Radio, Internet)	min = 1, **μ**= 3.83, **σ**= 1.46, max = 7
ATT08: DealerRel	Reliable source of information: Car dealer	min = 1, **μ**= 3.94, **σ**= 1.57, max = 7
ATT09: PersResRel	Reliable source of information: Personal research	min = 1, **μ**= 4.95, **σ**= 1.46, max = 7
ATT10: WorkSocialNetImp	Importance of input from work social network when purchasing a self-driving car	min = 1, **μ**= 3.92, **σ**= 1.76, max = 7
ATT11: NonWorkSocialNetImp	Importance of input from non-work social network when purchasing a self-driving car	min = 1, **μ**= 4.14, **σ**= 1.69, max = 7
ATT25: StatusImprove	Owning a self-driving car will improve individual's status among his peers	min = 1, **μ**= 2.92, **σ**= 1.94, max = 7
ATT19: LoseTies	Owning a self-driving car may result in losing friends who won't purchase self-driving car	min = 1, **μ**= 3.35, **σ**= 2.01, max = 7
ATT12: PoorInternet	Self-driving feature may fail under poor internet connection	min = 1, **μ**= 4.22, **σ**= 1.20, max = 7
ATT13: TakeOver	Driver should take over when CAV fails under poor internet connection	min = 1, **μ**= 4.31, **σ**= 1.16, max = 7
ATT14: SystemFailure	Unexpected operations of self-driving car due to operating system failure	min = 1, **μ**= 5.95, **σ**= 1.54, max = 7
ATT15: VirusAttack	Unexpected operations of self-driving car due to virus attack	min = 1, **μ**= 5.95, **σ**= 1.53, max = 7
ATT16: LessAgility	Lesser maneuverability and agility in auto driving mode of self-driving car as compared to standard car	min = 1, **μ**= 5.54, **σ**= 1.56, max = 7

Attribute notation if applicable	Description	Statistics (min, mean, std. dev. and max)
ATT17: FullControl	Computer will have full control over car	min = 1, **μ**= 5.31, **σ**= 1.67, max = 7
ATT18: LessSafe	A self-driving car might not be as safe as a standard car (the one you must operate)	min = 1, **μ**= 5.88, **σ**= 1.53, max = 7
ATT22: AnnMaint	Annual maintenance costs for a self-driving car may be a few hundred dollars more than for regular cars	min = 1, **μ**= 5.18, **σ**= 1.55, max = 7
ATT20: TSP	A self-driving car can be synced with traffic lights and other vehicles to decrease travel time	min = 1, **μ**= 5.11, **σ**= 1.59, max = 7
ATT21: Green	A self-driving car may generate less pollution compared to a standard car	min = 1, **μ**= 5.07, **σ**= 1.67, max = 7
ATT23: MobForDisabled	A self-driving car can provide more mobility for someone with a physical, visual, or other forms of impairment	min = 1, **μ**= 5.25, **σ**= 1.64, max = 7
ATT24: Multitask	An autonomous car can provide an increased level of productivity while traveling	min = 1, **μ**= 4.89, **σ**= 1.66, max = 7
ATT26: LessInsPrem	Having an autonomous car could decrease my car insurance premium	min = 1, **μ**= 5.31, **σ**= 1.53, max = 7
ATT27: SmartPark	Having an autonomous car could decrease time spent in parking the vehicle and monthly parking costs	min = 1, **μ**= 4.56, **σ**= 1.82, max = 7
-	Interested in using an autonomous taxi with the backup driver present	min = 1, **μ**= 3.38, **σ**= 1.98, max = 7
-	Interested in using an autonomous taxi with no backup driver present	min = 1, **μ**= 2.88, **σ**= 1.92, max = 7
-	Interested to own an autonomous car	min = 1, **μ**= 3.79, **σ**= 1.98, max = 7
-	Interested in sharing an autonomous car (carpool)	min = 1, **μ**= 3.09, **σ**= 1.89, max = 7
-	Interested in using an autonomous bus transit service (public transport)	min = 1, **μ**= 3.15, **σ**= 1.99, max = 7

Chapter 4 Methodology

To capture the individual's perceptions and intention to adopt CAVs, the statewide survey dataset was utilized in three different ways. Figure 4.1 showcases the entire methodological framework for the project. First, the dataset was utilized to generate the R-shiny web dashboard to visualize the survey results for a larger population (discussed in Section 3.2.1). The dataset was then split 70:30 for cross-validation purposes. Then the training dataset (70%) was utilized to model the hybrid choice modeling (HCM) framework (adapted from Sharma & Mishra, 2020b, 2020a) to capture the behavioral intention towards adopting different modes of CAVs. The test dataset (remaining 30%) was then used to perform a cross-validation, which ensured that the model did not overfit the data and was suitable for forecasting. A synthetic population was also generated from the survey dataset based on the current and future population forecasts for Tennessee. The current synthetic population (2020) was then used to forecast the statewide and county adoption rates. Then, an ABM approach was adopted from Talebian & Mishra (2018) to forecast the future adoption of CAVs over time while considering income levels and an annual reduction in the price of CAVs. The hybrid choice model was then applied to the future year synthetic population dataset. The ABM results were used to obtain the county adoption rate of CAVs for the state of Tennessee by 2050. The next subsections describe each modeling approach with the associated mathematical framework, wherever applicable.

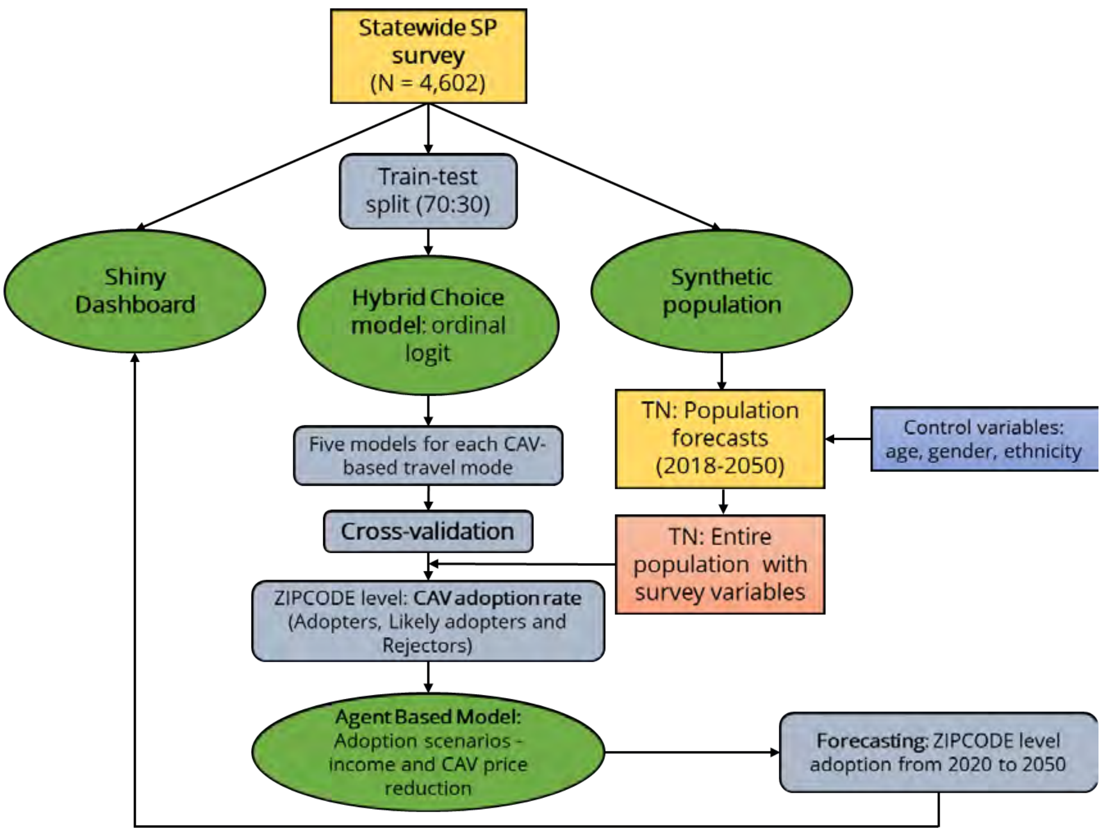


Figure 4.1
Methodological framework utilizing statewide survey dataset

4.1 Hybrid choice model

Choice models consider that a demand for a new product or technology innovation is the product of the decision of all the individuals in the considered population or sample size and follow the principle of random utility maximization. Decisions are made based on finite choices and finite attributes associated with them. These models also provide means to predict the future scenarios of a considered product or technology, optimizing its adoption and influencing or controlling its behavior. These models are based on four major assumptions: decision-maker, alternatives, associated attributes, and the decision rules (M. E. Ben-Akiva & Lerman, 1985). Depending on the number of outcomes or choices, choice models can be prefixed as binary (two alternatives) and multinomial (more than two alternatives). Normally, choice models utilize the data obtained through SP and RP surveys.

However, traditional choice models fail to capture the effect of unobserved or underlying attitudes and perceptions (Atasoy et al., 2013). Such underlying attitudes provide additional information in capturing the choice behavior(M. Ben-Akiva et al., 2002). Hybrid choice models are capable of capturing perceptions and attitudes in addition to observed information. HCM is a combination of SEM with DCM. Where the SEM framework estimates latent variables from attitudinal variables (M. Ben-Akiva et al., 2002), the DCM framework utilizes the estimated latent variables to capture their impact on the choice behavior. Since this project aims to capture the impact of individuals' attitudes towards the barriers and benefits associated with CAVs and the influence of peers in their social network on adopting CAVs, the HCM framework was utilized.

In the HCM framework, to identify the latent variables, first, an exploratory factor analysis (EFA) was employed to identify latent variables from the perception-related variables (measured on a 7-level Likert scale) delineated in Table 3.4. The SEM framework was then used to estimate the identified latent variables with a structural relationship with covariates delineated in Table 3.3 and a measurement relationship with associated Likert scale variables delineated in Table 3.4. In the DCM framework, the estimated latent variables were regressed along with other explanatory variables in the survey against an ordinal dependent variable: "residents interested to use a particular CAV-based travel mode (three levels: reject, will adopt, adopt))" while assuming error terms as logistically distributed, i.e., ordinal logit (OL). Then, the Monte-Carlo simulation was utilized to estimate the log-likelihood function, obtained as the probability of OL, conditional on the probability of the ordinal probit regression of latent variables. The maximum likelihood estimator is used to maximize the log-likelihood function.

4.1.1 Mathematical formulation

Mathematically, the two components of the HCM, the SEM (Equations 2, 3 and 4) and DCM (Equations 1 and 5), include separate equations for representing structural and measurement relationships between exogenous and endogenous variables, respectively (M. Ben-Akiva et al., 2002):

$$U_n = B\boldsymbol{x_n} + L\boldsymbol{x_n^*} + \varepsilon_n \qquad (1)$$

$$\boldsymbol{x_n^*} = A\boldsymbol{x_n} + \gamma_n \qquad (2)$$

$$\boldsymbol{i_{nr}^*} = D\boldsymbol{x_n^*} + \eta_n \qquad (3)$$

$$i_{nr} = \begin{cases} 1 \quad if\, \boldsymbol{i}^*_{\boldsymbol{nr}} \leq \tau_1 \\ 2 \quad if\ \tau_1 < \boldsymbol{i}^*_{\boldsymbol{nr}} \leq \tau_2 \\ \dots \\ j\ if\, \boldsymbol{i}^*_{\boldsymbol{nr}} > \tau_{j-1} \end{cases} \tag{4}$$

$$y_n = \begin{cases} o = 1 \quad if\, U_n \leq \mu_1 \\ o = 2 \quad if\, \mu_1 < U_n \leq \mu_2 \\ \dots \\ o = O\ if\, U_n > \mu_{o-1} \end{cases} \tag{5}$$

Equation 1 represents structural equations for the DCM framework where U represents utility for each individual, n ($n \in N$), explained by vector $\boldsymbol{x_n}$ $(K \times 1)$, consisting of K observable explanatory variables presented in Table 3.3; vector $\boldsymbol{x^*_n}(M \times 1)$, consisting of M unobserved latent variables identified from Likert scale variables in Table 5.1; and error terms, ε_n, assumed to be independently and identically distributed (i.i.d.), logistically distributed with Σ_ε as the covariance matrix. B and L are the matrices with coefficients of explanatory variables $(1 \times K)$ and latent variables $(1 \times M)$.

Equation 2 represents the structural equation for the SEM framework to calculate unobserved latent variable $\boldsymbol{x^*_n}$, described by explanatory variables $\boldsymbol{x_n}$ $(K \times 1)$ with its coefficient matrix A $(M \times K)$, reflecting the effect of $\boldsymbol{x_n}$over latent variables. γ_n is the vector $(M \times 1)$ of error terms assumed to be i.i.d. and normally distributed with φ as the covariance matrix. Many terms in $\boldsymbol{x_n}$ may be zero depending upon their association with latent variables.

Equation 3 represents the measurement equation for the SEM framework based on a vector of the random variable $\boldsymbol{i^*_{nr}}$ $(R \times 1)$, assumed to be normally distributed and discrete in nature (Likert scale with J levels) for each indicator ($r \in R$) and individual n (Table 3.4). The indicators are based on the vector of latent variables, $\boldsymbol{x^*_n}(M \times 1)$, estimated from equation 2 and matrix D $(R \times M)$, capturing the effect of the latent variables on indicators. η_n is the vector $(R \times 1)$ of error terms, assumed to be i.i.d. and normally distributed with ψ as the covariance matrix. Some terms in $\boldsymbol{x^*_n}$ may be zero depending upon the association of latent variables with the indicators. This association is identified using EFA, assuming the cut-off value of 0.4 (Pituch & Stevens, 2015). In Equation 4, the random variable $\boldsymbol{i^*_{nr}}$ is measured based on the observed vector of indicators and certain thresholds, τ_{j-1}, based on ordinal probit kernel where ($j \in J$). All the error terms (ε_n, γ_n and η_n) are assumed to be mutually independent. In this study, survey questions utilized a 7-level (J=7) Likert scale as shown in Table 3.4. Equation 5 represents the measurement equation for the DCM framework based on ordinal logit kernel as the dependent variable (section 3.2.4), y, is categorical with three ordered categories (O) and measured from utility (U) calculated in Equation 1 with certain thresholds μ_{O-1}.

4.1.2 Estimation

Hybrid choice models can be estimated through two different approaches: sequential and simultaneous. Sequential estimation involves estimating latent variables in the SEM framework first and then adding the estimated latent variables into the DCM framework. Second, the DCM framework is estimated through a maximum simulated likelihood function, conditional on latent and explanatory variables. In simultaneous estimation, both steps of sequential estimation are fused together (Joan Walker, 2001). Sequential estimation assumes independence between latent variables and the SEM framework and, hence, results in inconsistent estimates with measurement errors. Simultaneous estimation resolves this error but at the expense of increased computational effort and model complexity. Recent research indicates that there is no statistical difference between results obtained from both estimation approaches (Raveau et al., 2010). Therefore, due to the more straightforward and less computation effort and indifference in parameter signs and significance as compared to simultaneous estimation, sequential estimation is still preferred over simultaneous estimation (Anwar et al., 2014; Maldonado-Hinarejos et al., 2014; Nazari et al., 2018; Vredin Johansson et al., 2006). Hence, consistent with the recent literature (Anwar et al., 2014; Maldonado-Hinarejos et al., 2014; Nazari et al., 2018; Vredin Johansson et al., 2006), the hybrid choice model was estimated sequentially.

Therefore, first, the SEM framework's structural and measurement equations, conditional on each other, were estimated, followed by DCM framework's structural and measurement equations, conditional on explanatory and estimated latent attitudinal variables. The joint density, or likelihood, function for the SEM framework is given by:

$$\mathcal{L}(\boldsymbol{I_n}|\boldsymbol{x_n}; D, A, \psi, \varphi) = \int_{x^*} f_{i^*}(\boldsymbol{i_{nr}^*}|\boldsymbol{x_n^*}; D, \psi)\, f_{x^*}(\boldsymbol{x_n^*}|\boldsymbol{x_n}; A, \varphi)\mathrm{d}x^* \tag{6}$$

The first term of integrand represents the measurement equation of the SEM framework, and the second term represents the structural equation of the latent variable. The joint probability of both equations is integrated over a vector of the latent construct, x^*, as the latent variables follow this distribution. The latent variables x_n^* estimated from Equation 6 are plugged into the following likelihood function of the DCM framework:

$$\mathcal{L}(y_n|\boldsymbol{x_n}, \boldsymbol{x_n^*}; B, L, \Sigma_\varepsilon) = \int_{x^*} f_y(y_n|\boldsymbol{x_n}, \boldsymbol{x_n^*}; B, L, \Sigma_\varepsilon)\mathrm{d}x^* \tag{7}$$

Where the density function, $f_{y,}$ is estimated the ordinal logit kernel based on Equation 5. The integral in Equation 7 can be evaluated using the Monte Carlo simulation method with 150 Halton draws. Then, the resulting likelihood was estimated using maximum simulated likelihood (MSL).

4.2 Agent-based model

Simulation techniques such as ABM are another type of disaggregate method which are becoming more popular in the modern world because of their level estimation (El Zarwi et al., 2017). ABM works on a bottom-up technique that rests on interactions and actions of multiple heterogeneous elements of an overall system to study their multilevel effect on the environment, system, or the elements themselves. ABM considers attributes related to the system building elements. The focus is on the complex interactions and actions of these elements, and these elements are usually referred to as actors or agents. ABM includes the advantages of its flexibility in incorporating emerging phenomena and the ability to formulate real-world characteristics. ABM rests on three methodological pillars, namely modeling, agents, and simulation. ABM can be used in two ways: either studying the impact of micro-level elements over macro-level or studying macro-level interactions over micro-level elements (Müller, 2016). Limitations of ABM include disadvantages in complexity in the formulation of all the real-world characteristics and requiring powerful machines (computers) to complete the simulation. ABM also fails to account for the behavioral interactions between agents (Müller, 2016).

The methodological approach for capturing the evolution of adoption rates for CAV-based travel modes was adopted from Talebian & Mishra (2018), i.e., an agent-based model, to predict the future market share of CAVs as illustrated in the upcoming subsections. The adoption process of an individual is based upon the concept of resistance, which includes two barriers, namely functional and psychological. Functional barriers cover the effect of adopting a novel technology over a daily routine or habits. In contrast, psychological barriers include the effect on an individual's prior beliefs. The model includes three main steps: (i) Mass communication model, (ii) Pre-introduction vehicle purchase model and (iii) Social network communication model.

4.2.1 Mass communication model

This model captures the impact of individuals' exposure to the advertisements, while listening to Radio or TV, on their perceptions towards CAVs, hence referred to as "mass communication model". The model assumes that a person's decision to purchase a CAV depends on their perceptions of the product's various attributes. Perceptions are assumed to be dynamic as they change based upon the exposure to additional information through media or peers in a person's social network. Hence, the change in perceptions is given by

$$P_{i,l}^{t} = P_{i,l}^{t-1} + K_{i}^{t,t-1} \frac{P_{i,l}^{t} \varepsilon_{i,l}}{(1+\delta)^{\lambda_{t-1}^{l}}}, \forall \mathrm{l} \in \mathrm{L}, \mathrm{t} = 1,2,3, \ldots, \mathrm{T}, \mathrm{i} \in \mathrm{I} \tag{8}$$

Where, $P_{i,l}^{t}$ is the perception of an individual towards *l*[th] element at time *t*; *L* is the set of all elements associated with CAVs; *I* is the set of individuals/agents; $K_{i}^{t,t-1}$is a binary dummy variable indicating the exposure of an agent to the media or information between time interval *t* and *t-1*; $\varepsilon_{i,l}$, defined as (0,1), denoting the impact of information obtained on the agent's perception towards lth element; δ $d$enotes the dissipation rate of information obtained through media; and λ_{t}^{l} captures the frequency of exposure of the agent to the media (TV or radio).

4.2.2 Pre-introduction vehicle purchase model

This model captures an individual's intention to purchase a new vehicle based on their existing vehicle's lifetime and purchasing frequency before the CAVs are available in the market. Hence it is referred to as Pre-introduction vehicle purchase model. The model's algorithm is as follows:

i. At t=0, for each individual, age of the presently owned vehicle, a_{i}^{0}, is assumed to be uniformly distributed, i.e., $U(0, E_{i})$ where E_{i} is drawn from truncated normal distribution $N(\mu, \sigma)$ $with$ $\max = M$ and $\min = 0$.
ii. At, t = t+1, $a_{i}^{t} = a_{i}^{t-1} + 1, \forall \mathrm{i} \in \mathrm{I}$
iii. If $a_{i}^{t} > E_{i}$, agent *i* buys a new vehicle and $a_{i}^{t} = 0$ and $E_{i} = N(\mu, \sigma)$
iv. Steps i to iii are repeated until $t < Tb$, *where Tb is the* length of the pre-introduction period and $a_{i}^{Tb}$is the final output.
v. Agent purchases a new vehicle if

$$a_{i}^{t} > E_{i} \text{ or } a_{i}^{t} = frequency\ of\ car\ purchase$$

The frequency of car purchases for each agent can be obtained from the survey dataset.

4.2.3 Social network communication model

This model captures the impact of a peer-to-peer communication on the decision to adopt CAVs and hence referred to as social network communication mode. The model assumes that this impact depends on the number of peers and frequency of communication with them. The WOM concept is introduced as part of social communication, which can be either positive or negative based on the nature of the interaction of agents with their peers. The social impact is given by

$$P_{i,l}^{t} = P_{i,l}^{t-1} + \sum_{j \in F_i} s_{ij}^{t} \frac{u_{ij}\eta_{ij}^{l}(P_{i,l}^{t} - P_{i,l}^{t-1})}{(1+\omega)^{v_i^t - 1}}, \forall\ l \in L, t = 1,2,3, \dots, T, i \in I \quad (9)$$

Where, $P_{i,l}^{t}$ is the impact of social interaction on the perception of individual towards *l^th* element at time t; L is the set of all elements associated with CAVs; I is the set of individuals/agents; F_i is the set of *j* number of peers in agent $i's$ social network; s_{ij}^{t} is a binary dummy variable indicating whether the agent communicated with the peers between period *t* and *t-1*; η_{ij}^{l}, defined in (0,1), denotes the effect of communication between agents i and *j* between time t and $t-1$ on agent $i's$ perception towards lth element; ω $d$enotes the dissipation rate of WOM; and v_i^t captures the frequency of communication of agents i and *j*.

The model also captures the impact of negative WOM from adaptors to the potential buyers after multiplying the positive influence values of η_{ij}^{l} by (-1). Finally, u_{ij} is the strength of social connection between agents i and *j,* which is obtained from the synthetic social network between agents. The social network is developed based on the homophily principle: making a link between two agents if they share similar geographical and socio-demographic characteristics. The distance between two agents and the weight of the connection in a social network is given by

$$d_{ij} = \sqrt{\sum_{o \in Z} \pi_o \left(\frac{H_{o_i} - H_{o_j}}{maxH_o}\right)^2} \quad (10)$$

$$u_{ij} = \frac{d_{ij} - min_j d_{ij}}{max_j d_{ij} - min_j d_{ij}} \quad (11)$$

Where Z is the set of *m* socio-demographic and geographic characteristics, H_o and π_o are scores and weights for characteristic *o*, d_{ij} is the distance of social connection between two agents i and j. u_{ij} is the weight defined as [0,1], where 0 indicates a weak connection, and 1 indicates a strong connection. For more details, the reader is referred to Talebian & Mishra (2018) on generating social networks. Finally, it is also assumed that the WTP to buy a CAV is also affected by social interaction, and it is given by:

$$Pur_i^t = Pur_i^{t-1} + \sum_{j \in F_i} \frac{u_{ij}\psi_{ij}(Pur_j^{t-1} - Pur_i^{t-1})}{(1+\omega)^{v_{i,j}^t - 1}}, \forall\ t = 1,2,3, \dots, T, i \in I \quad (12)$$

Where, Pur_i^t represents the impact on agents' WTP to buy a CAV due to social interaction at time t; ψ_{ij}defined in [0,1], denotes the effect of communication between agents i and j on agent i's WTP. At any time, t, each agent willing to buy CAVs has a perception index:

$$TP_i^t = \sum_{l \in L} \tau_l P_{i,l}^t \quad (13)$$

Where τ_l is the weight of each perception element. If the age of the present vehicle is equal to E_i or the car purchasing frequency and WTP to buy a CAV is greater than its purchasing price, the agent compares its perception index, TP_i^t, with a predefined threshold χ_c and decides between purchasing the CAV or a conventional vehicle. After the decision, the simulation continues for each agent and all periods while constantly updating perceptions towards associated elements and WTP towards CAV. Since this research aims to quantify the market share of CAVs, the value of all parameters was assumed to be the same as Talebian & Mishra (2018).

From the model proposed by the authors, a price reduction scenario was utilized where the purchase cost of the CAVs is assumed to decrease annually by 5%, 10%, 15%, and 20%. The model was then applied to the survey dataset to obtain the proportion of individuals who were willing to change their decision from “reject” to “will adopt” or “will adopt” to “adopt” based on their income levels. This approach was opted for forecasting due to computational memory limitations because the research team could not apply the agent-based model to the entire synthetic population data. To generate and store social network data for the entire state, it would take about a year in a 64GB RAM machine.

4.3 Synthetic population

A person-level synthetic population was generated based on the survey dataset for the entire state of Tennessee using a synthetic reconstruction approach. The approach uses an iterative proportional updating (IPU) algorithm, which reallocates and adjusts weights among a particular type of household until household- and person-level attributes are matched with the marginal distributions (Konduri et al., 2016). The population forecasts for Tennessee in 2020 and 2050 were obtained from Tennessee State Data Center (2019). From both datasets (survey and population forecasts), socioeconomic characteristics, age, gender, and ethnicity were used as the matching attributes. A five-digit ZIP code of respondents' home location from the survey dataset and census tract from population forecasts were utilized to match the geographical location of survey respondents and population. For this purpose, a ZIP code to tract-level crosswalk was obtained from Din & Wilson (2020). Lastly, software PopGen (Konduri et al., 2016), survey dataset, and population forecasts were used to inflate the sample of 4,602 individuals to the entire population of Tennessee from 2020 through 2050.

Chapter 5 Results and Discussion

5.1 Hybrid choice model

This section scrutinizes results of the hybrid choice model and discusses the key findings from the CAV adoption perspective. 70 percent of the dataset was utilized for training the model and the remaining 30 percent for testing the model against overfitting.

5.1.1 Exploratory Factor Analysis results

The EFA model, crucial in identifying the underlying attitudes among the residents, was estimated in the software Mplus. Some preliminary checks were applied on the data for its suitability for the factorability (Bartlett's test of sphericity: chi-squared = 42,859.14 at p =0.0) and sample adequacy (Kaiser-Meyer-Olkin test: 0.91 > 0.6). A scree-plot analysis was then performed to identify the number of factors that could be retained (factors with an eigenvalue > 1). The model was estimated using the VARIMAX orthogonal rotation and maximum likelihood method. All six factors had a meaningful association with the Likert scale indicators and explained 55% variance in the sample. The goodness fit indices for the EFA model were the standardized root mean square residual (SRMR) equals 0.021 (<0.08 as per Hu and Bentler (1999)), root mean square error of approximation (RMSEA) equals 0.056 (<0.06 as per Hu and Bentler (1999)), comparative fit index (CFI) is 0.951 (>0.95 as per Hu and Bentler (1999)), and chi-squared test equals 42,976.77 (df =351, p-value =0). As per the two-index presentation strategy given by Hu and Bentler (1999), the model indicates a good fit (RMSEA and SRMR). Being consistent with the literature (Pituch & Stevens, 2015), a cut-off value of 0.4 was used to retain the factor loadings, explaining the association of latent variables with the Likert scale indicators.

The six factors, along with their respective loadings, are shown in Table 5.1. The bold values in the table satisfy the cut-off criteria and were used to name the factors (referred to as latent variables hereafter) as per the nature of the associated indicators. CAV Barriers (CBar) represent the worrying concern of respondents towards the anticipated barriers of the CAVs. CBar is related positively with all the negative impacts of CAVs like autonomous driving failure under poor internet connection, system failure, and virus attack. The variable was also related directly to CAVs being less safe, less agile, and more expensive to maintain than conventional cars. Similarly, the latent variable CAV Benefits (CBen) represents the resident's attitude towards the positive aspects of the CAVs, such as multitasking, lower insurance premiums, smart parking functionality, and travel time savings at road intersections. CAV purchase (CPur) emulates the residents' attitude towards the importance of purchase-related characteristics of CAVs like price, quality, environmental friendliness, and ability to make self-service station trips. Social Status (SS) captures the residents' perception of the impact of adopting a CAV on their personal image and status among the peers in their social network. Social influence (SI) represents the resident's importance to the CAV-related information received from their peers at work and non-work social network in their decision to purchase a CAV. Finally, Media Influence (MI) represents the residents' attitude towards the reliability of CAV-related information received from media and car dealers when purchasing a CAV.

Table 5.1
Exploratory factor analysis: results (N= 3,221)

Indicator variable	CAV Barriers	CAV Benefits	CAV Purchase	Social Status	Social Influence	Media Influence
ATT01: CarPrice	0.224	0.062	**0.760**	-0.086	0.076	0.003
ATT02: CarQuality	0.232	0.037	**0.858**	-0.035	0.037	-0.007
ATT03: Environment	0.055	0.208	**0.432**	0.180	0.024	0.166
ATT04: PersonalImage	-0.065	0.110	0.117	**0.466**	0.099	0.171
ATT05: ServiceStationTrips	0.222	0.159	**0.538**	0.010	0.041	0.062
ATT06: FriendRel	0.220	0.194	0.172	-0.130	**0.487**	0.289
ATT07: AdvtRel	0.048	0.184	0.075	0.179	0.230	**0.776**
ATT08: DealerRel	0.090	0.105	0.041	0.251	0.146	**0.663**
ATT09: PersResRel	0.242	0.268	0.151	-0.115	0.328	0.335
ATT10: WorkSocialNetImp	0.004	0.128	0.014	0.274	**0.746**	0.120
ATT11: NonWorkSocialNetImp	0.058	0.147	0.027	0.162	**0.699**	0.128
ATT12: PoorInternet	**0.655**	0.230	0.170	-0.121	0.109	0.054
ATT13: TakeOver	**0.746**	0.228	0.185	-0.141	0.108	0.071
ATT14: SystemFailure	**0.823**	0.225	0.181	-0.182	0.121	0.043
ATT15: VirusAttack	**0.809**	0.225	0.145	-0.134	0.086	0.041
ATT16: LessAgility	**0.752**	0.136	0.141	0.097	0.014	0.063
ATT17: FullControl	**0.636**	0.109	0.080	0.173	0.026	0.034
ATT18: LessSafe	**0.791**	0.167	0.112	-0.037	0.024	0.039
ATT19: LoseTies	0.077	0.061	-0.048	**0.702**	0.066	0.044
ATT20: TSP	0.311	**0.620**	0.158	0.015	0.163	0.102
ATT21: Green	0.310	**0.573**	0.147	0.088	0.076	0.151
ATT22: AnnMaint	**0.518**	0.280	0.143	0.099	-0.029	0.055
ATT23: MobForDisabled	0.370	**0.563**	0.125	0.057	0.081	0.109
ATT24: Multitask	0.187	**0.669**	0.076	0.197	0.159	0.089
ATT25: StatusImprove	-0.151	0.217	-0.063	**0.728**	0.109	0.115
ATT26: LessInsPrem	0.359	**0.611**	0.104	0.014	0.111	0.075
ATT27: SmartPark	0.104	**0.644**	0.045	0.277	0.104	0.071

Note: Bold values indicate loadings > 0.4 (Pituch & Stevens, 2015)

5.1.2 Structural equation modeling results

The SEM framework relates the identified latent variables or attitudes of residents with their sociodemographic and other attributes. We utilized the training data to estimate the model using the python module "Pandasbiogeme" (Bierlaire, 2018) and R package "lavaan" (Rosseel, 2012). For brevity and ease in presentation, the results of the SEM framework's structural and measurement equations are presented in Table A.1 and Table A.2 in Appendix A. The goodness of fit indices for the SEM framework are: adjusted McFadden's ratio is 0.472; SRMR equals 0.054 (<0.08 as per Hu and Bentler (1999)); RMSEA equals 0.032 (<0.06 as per Hu and Bentler (1999)); chi-squared test is 207,722.89 (df = 325, p-value =0) (Golob, 2003); Tucker-Lewis index (TLI) equals

0.995 and CFI is 0.963 (>0.95 as per Hu and Bentler (1999)). Adjusted McFadden's ratio (varies between 0 to 1) can be interpreted as improvement of the final model over the intercept only model (McFadden, 1974). The model fit improves when the value of the adjusted McFadden ratio increases. Hence in addition to adjusted McFadden's ratio, as per the two-index presentation strategy proposed by Hu and Bentler (1999), the model indicates indices good for individual fit and combinations of those indices (RMSEA-SRMR and TLI-SRMR).

Among the structural equation results, the positive (negative) sign of the coefficient can be interpreted as concern (unconcern) towards the associated latent attitude. In contrast, the magnitude of the coefficient represents the intensity of the relationship. Individuals of all ages are concerned about their social status (except for the elderly), influenced by CAV-related information received from the media, and give importance to the benefits, price, quality, and environmental friendliness of CAVs. Such a finding is as expected because the individuals planning to adopt CAVs will be looking for CAV-related information and will consider CAVs as a status symbol among their peers. This finding highlights the importance of running the advertisements related to the benefits and attractive price of CAVs and portraying CAVs as status seeking symbols are consistent with Weiss & Fershtman (1998). Elderly individuals do not believe that CAVs will increase their social status as they might use CAVs as a passenger rather than an owner. Literature also highlights the negative relationship between age and status seeking attitude (Weiss & Fershtman, 1998a). As compared to females, males do not believe that CAVs will improve their social status and are not influenced by CAV-related media advertisements but consider barriers and purchase-related characteristics important. This might be due to generally higher tech awareness and exposure among males than females (Singh, 2019).

White people and residents from other ethnicities do not believe that CAVs will positively impact their social status. Residents finishing high school or below are not concerned about the CAV barriers because of their excitement towards the latest technology. Residents completing some college do not believe that CAVs will affect their social status. Such residents are influenced by CAV-related information received from their peers. Similarly, highly educated residents do not believe that CAVs will increase their social status as they might be aware of the technological benefits of CAVs (Quazi & Talukder, 2011). Resident's marital status has no differentiating effect on their attitude towards social status associated with CAVs. Individuals who never watch TV or use smart home services were not concerned with the social status impact of CAVs. Tech-savviness captured from the frequency of using smart home services and GPS navigation (consistent with Seebauer et al. (2015)) showed expected results as non-tech-savvy individuals are not concerned about impact of CAVs on their social status because of their decreased dependence on technology. These findings illustrate the importance of being aware of latest smart technology on the positive attitude towards CAVs.

Annual personal income was related positively with all latent attitudes, whereas the magnitude of coefficients was as expected. For instance, individuals earning less than $35,000 are more concerned about the benefits and purchase-related characteristics of CAVs than residents earning between $35,000 and $75,000. This is consistent with their affinity to get more utility for the money they decide to spend on CAVs. These results align with existing literature (Bansal et al., 2016; Howard & Dai, 2014; Kyriakidis et al., 2015). The latent attitude Social Status, associated with CAV purchase, is positively related with all income levels and higher-income individuals are more concerned than low-income earners which highlights that wealthy people perceive CAVs as status symbol. The finding is well supported by increase in individual's social status seeking attitude with an increase in their income (Jin et al., 2011; Weiss & Fershtman, 1998a). The latent variable Social Influence is related positively with low-income individuals highlighting that such individuals are more influenced by their peers, in line with existing literature (Micheli, 2016). The annual household income also showed similar results as personal income with the latent constructs Social Status and Social Influence. Frequency of purchasing a car, willingness to pay towards buying a conventional car, willingness to pay towards adding autonomous technology to existing vehicles, willingness to pay towards annual maintenance of CAVs, frequent users of a private car for the daily commute, frequent users of ride-haling services and infrequent users of public transport showed favorable results in their attitude towards CAV purchasing characteristics. Such results show that residents will pay attention to the price, quality, and other characteristics of CAVs when looking to buy a new car.

Individuals with a smaller number of peers knowledgeable about cars are influenced by CAV-related information obtained from media but not from their peers, which is because such individuals do not have another source. Similarly, individuals with an increased number of peers and peers knowledgeable about cars are more likely to be influenced by the CAV-related information received from their social network (consistent with Sharma & Mishra (2020)) and less influenced by media advertisements. As expected, individuals communicating regularly with their peers are more likely to be influenced by them when purchasing a CAV.

Physically disabled individuals are more concerned about the CAV-purchase-related information as they might purchase CAVs to complete their mobility needs. Individuals familiar with CAVs are concerned about their negative impacts and purchasing characteristics. Such individuals might be interested in adopting CAVs being consistent with previous literature (König & Neumayr, 2017; Kyriakidis et al., 2015; Penmetsa et al., 2019; Saeed et al., 2020; Sweet & Laidlaw, 2019).

Table A.2 in Appendix A delineates the results for the measurement equation component of the SEM. One of the associated indicators with latent variables was fixed to zero for estimation and interpretation purposes (base). For latent variable, SS, indicator capturing resident's perception towards the possibility of losing peers who will not purchase a CAV if resident adopts a CAV (ATT19) was kept as a base. For latent variable SI, residents' perception towards the importance of information received from non-work peers when purchasing a CAV (ATT11) was kept as reference. For latent variable CBar, residents' concern towards giving the computer full control of the vehicles (ATT17) was kept as a base indicator. Latent variable CBen, residents' perceptions towards the environmental friendliness of CAV (ATT21), was set as reference. For CPur, residents' perception towards quality of car when purchasing a CAV (ATT02) was kept as a base. Finally, latent variable MI, residents' perception towards the reliability of CAV-related information received from car dealers (ATT08), was kept as base. Column 3 in the table includes each indicator's estimated coefficient along with the statistical significance. The estimates can be interpreted as: if individuals believe that CAVs will improve their social status, they are concerned about improvement in their social status and personal image compared to the possibility of losing friends who do not adopt CAVs. This result is synonymous with Acheampong and Cugurullo (2019). As compared to receiving CAV-related information from non-work peers, individuals find their friends more reliable than information received from peers at work. Existing literature

(Brown et al., 2014; Jing et al., 2019; Liu, Yang, et al., 2019; Panagiotopoulos & Dimitrakopoulos, 2018) reported similar results in terms of the positive impact of social influence on CAV adoption. Individuals place higher importance on all negative aspects of CAVs like the failure of CAVs under virus attacks, system failure, and poor internet connection. Individuals were concerned about trusting autonomous technology with driving location-related data, which is in line with Brell et al. (2019). We did not find any significant result for the latent variable CAV Benefits and its indicators. Regarding car quality, individuals consider price, environmental friendliness, and automated trips to service stations more important. For the latent variable Media Influence, individuals found car-related information received from car dealers more reliable than media advertisements which can be attributed to personalized service in a car dealership during a test drive or visit.

5.1.3 Discrete choice modeling results

After estimating the latent variables, the five different ordinal logit models were embedded for each CAV-based travel mode, i.e., privately owned CAVs, carpooling a CAV, CAV-based public transit, CAV-based ride-hailing service with and without a backup driver. The dependent variable in each model was residents' intention to use CAVs using three levels: Reject, Will adopt, and Adopt. The models were estimated in the R package "MASS" (Ripley et al., 2013). For brevity, the tabulated results for residents' intention to adopt a privately owned CAVs and remaining four modes are in Appendix A. All insignificant variables (p-value>0.10) were excluded. This section discusses the key results from all five models. For interpretation purposes, the positive (negative) sign of the coefficients signifies the intention to adopt (reject). The magnitude of the coefficient represents the intensity.

5.1.3.1 Privately-owned CAVs

The privately-owned CAV model resulted in an adjusted McFadden's ratio of 0.16 (highlighting the improvement in the goodness of fit of the final model compared to the intercept-only model) and a final log-likelihood of -2,485.53. The key results are portrayed in Figure 5.1. Elderly individuals are less likely to adopt CAVs as compared to the younger residents. This can be due to their distrust of the technology. The result is consistent with existing studies (Liu, Zhang, et al., 2019; Robertson et al., 2017). Residents up to date with the latest smart technology (captured from the frequency of using smart home services and GPS navigation systems consistent with Seebauer et al. (2015)) are more likely to adopt privately owned CAVs. This is because of the propensity of such residents to be excited about technological innovations and more likely to be the early adopters. This result is in line with the findings of Lavieri et al. (2017). Residents who bought one or more cars in the last ten years are less likely to adopt privately owned cars because it might be early for them to buy another vehicle and might not be in the market for a new car. This result is well supported by the finding of residents planning to purchase a car in the next three years are more likely to adopt a CAV. A flexible work schedule is related positively to the intention to ride in a privately-owned CAV, which is in line with existing literature (Nazari et al., 2018). As expected, residents willing to pay higher for autonomous technology are more likely to adopt privately owned CAVs meaning such individuals might be among the early adopters of CAVs. Finally, as far as the impact of attitudes on residents' intention to adopt a privately owned CAV is concerned, residents who believe that CAVs will increase their social status are more likely to adopt privately owned CAVs. Similarly, residents who are influenced by CAV-related information received from their peers are more likely to adopt CAVs. These results are in line with existing literature (Leicht et al., 2018; Nordhoff et al., 2018; Panagiotopoulos & Dimitrakopoulos, 2018). Residents who consider CAV purchasing-related characteristics like price, quality, and ability to make self-trips to service stations are more likely to adopt CAVs in line with Acheampong et al. (2021).

5.1.3.2 Sharing/Carpooling a CAV

The sharing/carpooling a CAV model resulted in an adjusted McFadden's ratio of 0.15 and final likelihood of -1,906.71. Among the results, compared to females, males were more likely to share a CAV consistent with increased safety constraints associated with females (Lavieri et al., 2017). As expected, single residents are more likely to share the CAVs than married, separated, divorced, or widowed individuals, which can be due to no constraints from family and individual benefits of sharing the CAV to split fuel costs with other passenger (s). Individuals whose households purchased more than three vehicles in the last ten years are less likely to carpool. It can be attributed to the households' desire to save more money before making another large investment since selling a newer vehicle will not be worth the trade-off of driving it for a few more years. Individuals frequently working from home are more likely to carpool a CAV. This could be because, such residents will require a car for a short period of time and can carpool with one of their family members or peers. The finding supports another finding that long-distance travelers and regular users of private cars are less likely to carpool a CAV. The individuals communicating with their peers, every couple of weeks, are also more likely to carpool a CAV as they might pair with their peers for their daily commute or dining out trips. Interestingly, we find a positive effect of all latent variables (except the CAV Barrier) on their intention to carpool a CAV. This is consistent with their increased attitude towards social status and influence from their peers when carpooling a CAV. Such individuals also may be likely to pay more attention to the benefits and media-related information of CAVs.

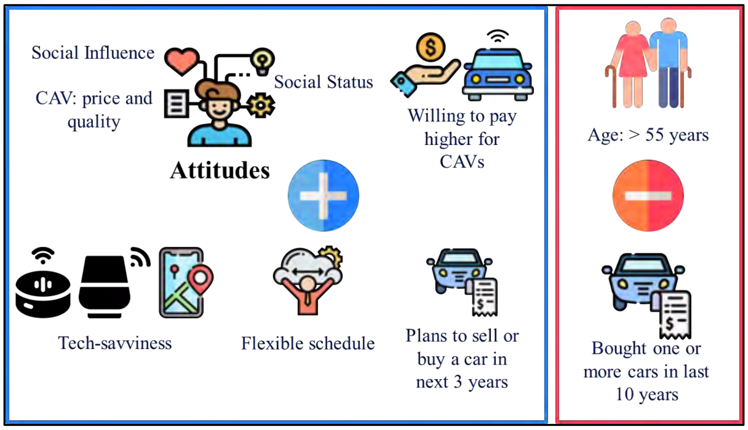


Figure 5.1

Key findings related to residents' intention to adopt privately owned CAVs

5.1.3.3 CAV-based public transit

The carpooling CAV model resulted in adjusted McFadden's ratio of 0.13 and final likelihood of -2,088.71. Results indicate that, compared to females, males are more likely to adopt CAV-based public transit, which can be associated with safety constraints. As compared to other ethnicities, Whites and African Americans are less likely to use CAV-based public transport which can be due to the increased transit dependence of other ethnicities in line with existing literature (Blumenberg & Shiki, 2007; Granados et al., 2021; Rosenbloom, 1998). Hence, they will be inclined to use CAV-based public transport. Being familiar with the latest smart technologies is related positively to use CAV-based public transit. Urban residents are more likely to use CAV-based public transport than rural counterparts, which can be due to the higher transit coverage in urban areas. As expected, long-distance travelers are less likely to use CAV-based public transport. Residents using conventional public transit for their daily commute are more likely to adopt CAV-based public transit, which is obvious. Individuals willing to pay more for autonomous technology are more likely to use CAV-based public transit due to their increased interest in CAVs and being early adopters. Like the results of owning and carpooling a CAV, all attitude constructs had positive impacts on the resident's intention to use CAVs, reflecting that the adoption of CAV-based public transit is associated with general increased social status influence from peers and media. Such residents are also concerned about the positive, negative, and price-related aspects of CAVs.

5.1.3.4 CAV-based ride-hailing service (with and without backup driver)

The CAV-based ride-hailing service with a backup driver resulted in an adjusted McFadden's ratio of 0.14 and final likelihood equal to -1,782.47. In contrast, the without backup driver model reported adjusted McFadden's ratio of 0.10 and final likelihood equal to -2,328.27. Like other CAV-based travel modes, tech-savviness was related positively with residents' inclination to use any ride-hailing services. As expected, urban residents are more likely to adopt CAV-based ride-hailing services, which can be attributed to the high coverage of ride-hailing services in such areas. The residents who purchased two or more new cars in the last ten years are less likely to use CAV-based ride-hailing services with a backup human driver present which can be due to their propensity to drive their purchased cars. This result is well supported by a lower likelihood of residents to employ such ride-hailing service if they use private car for their daily commute.

Interestingly, residents using conventional ride-sharing services for their daily commute are more likely to use CAV-based ride-hailing services with a backup human driver present. Like other CAV-based modes, residents with increased WTP for the autonomous technology are more likely to use CAV-based ride-hailing services, which can be attributed to their willingness to become early adopters at higher prices in the initial stages. Interestingly, residents with a past accident involvement are not as interested in using a CAV-based ride-hailing service with no backup human driver as they might not trust autonomous technology with driving in a shared mobility setting and might prefer a backup human driver in the initial stages. Like other modes, all attitude constructs positively impacted residents' inclination to adopt CAV-based ride-hailing services.

5.1.3.5 Marginal effects for all five models

The marginal effects were also estimated for all five models and the results are delineated in Appendix A (Table A.5 to Table A.9). The first column of the table includes variables with their levels. The remaining three columns include marginal effect coefficients for each category of the dependent variable, i.e., "Reject," "interested," and "Fully adopt." The positive (negative) sign in the coefficients increases (decreases) the likelihood of falling in a specific outcome when there is a unit change in the considered variable. The magnitude, when multiplied by 100, gives the percentage change in the likelihood. The bold values in the columns indicate the maximum and minimum coefficients for each level of dependent variables. Among the results, for privately owned CAVs, if an individual earns income between $35,000 and $100,000, the likelihood of adopting and rejecting a CAV increases and decreases by 2% and 9%, respectively. If individuals are concerned about the price, quality, and environmental friendliness of CAVs, then their likelihood to adopt and reject increases and decreases by 21% and 80%.

Similarly, for carpooling a CAV, if individuals are influenced by information from social networks, their likelihood of adopting and rejecting increases and decreases by 6% and 37%. For CAV-based public transport, if individuals are concerned about their social status, their likelihood to adopt and reject increases and decreases by 8% and 37%, respectively. Similar results are obtained for CAV-based ride-hailing service with a backup human driver present where concern towards social status increases and decreases the likelihood of adoption and rejection by 9% and 49%. Finally, for CAV-based ride-hailing service without a backup human driver present, if individuals are concerned about CAV's price, quality, and environmental friendliness, their likelihood to adopt and reject increases and decreases by 11% and 47%.

5.2 Agent-based model

The agent-based model was coded in MATLAB while utilizing the entire survey dataset to run the simulation. The simulation captured the impact of the annual price reduction of CAVs on their market share. It is consistent with the anticipation that in the initial stages, CAVs will be expensive. Governmental policy incentives like vehicle registration discounts, reduced annual renewal costs, and tax rebates have great potential to boost CAV adoption. It was assumed that from 2025 onwards, there would be an annual reduction in the price of CAVs. Then the market share of CAVs was predicted until 2050. Since the car purchasing frequency in the survey dataset represents two weeks, the same time unit was kept for one iteration. The model was simulated for 650 iterations (2025 to 2050 with a step size of two weeks), modeling four price reduction scenarios, i.e., 5% to 20% with 5% as the step size.

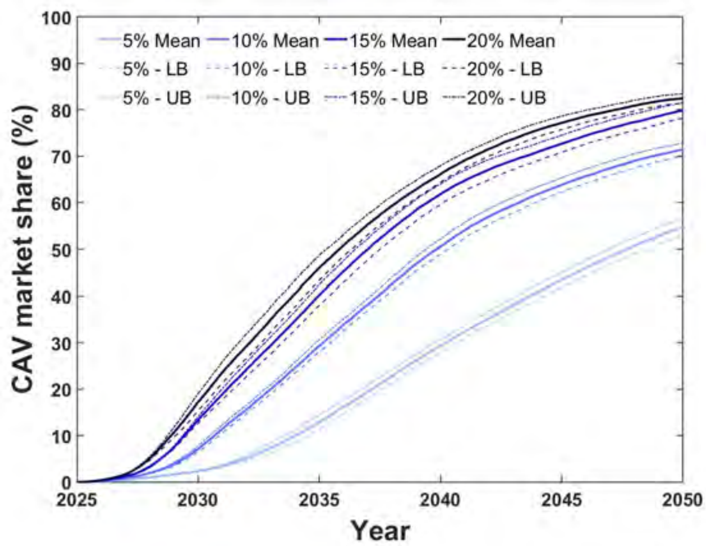


Figure 5.2
Agent-based model results: CAV market share under four scenarios of price reduction

The parameter values for the scenario in the methodological framework were as follows: effect of communication between two agents i and j on agent i's WTP i.e., $\psi_{ij} \sim U\ (0,0.5)$; effect of communication between two agent i and j agent i's perception of perception element l i.e., $\eta_{ij}^{l} \sim U(0.5,1.0)\ \forall l \in L$; and impact of information obtained on the agent's perception towards element l i.e., $\varepsilon_{i,l} \sim U(0.3,0.4)\ \forall l \in L$. Figure 5.2 shows the mean market share and the upper and lower bounds at a 95% confidence interval in all four scenarios. With a 5% reduction, about 55% of the respondents will adopt CAVs, whereas, with a 20% reduction, the adoption rate will increase to 83%. For a 5% increment in the annual price reduction i.e., 5% to 10%, the market share of CAVs in 2050 increases from 55% to 70%. From these results, the proportion of respondents who were more likely to adopt the CAVs over time, segregated by their income levels, was obtained. Such respondents will choose to go from non-adopting CAVs to adopting them based on the annual price reduction and their personal income. These findings were used in the results of statewide predictions of the hybrid choice model to obtain the adoption levels of all CAV-based travel modes by 2050. These adoption levels are discussed in the next section. This approach of forecasting was adopted because of difficulties in applying the agent-based model to the entire synthetic population data due to computational memory limitations.

5.3 How many individuals will adopt a privately owned CAV?

Table 5.2 delineates the cross-validation for all five hybrid choice models. The F-1 score captures the model's accuracy in a test dataset (30% of the entire dataset). All models returned a score of at least 0.63, which ensures that the model is not overfitting the training data and can be used for forecasting. The next step required applying the HCM framework to the statewide synthetic population dataset (from 2020 to 2050) to forecast the future adoption rates. The HCM framework captured the static adoptions every year. The results of the agent-based model were used to identify the individuals who will adopt the CAVs over time based on their income and the annual price reduction of CAVs. The upcoming subsections discuss the adoption results for all CAV-based travel modes results at both the state and county levels.

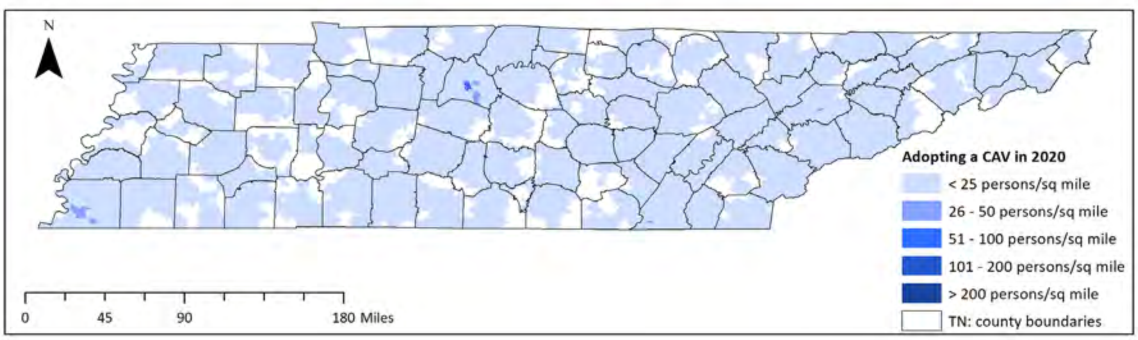
Table 5.2
Cross-validation results for hybrid choice models (N= 1,381)

Models for each CAV-based travel mode	Precision	Recall	F1-score
Own a CAV	0.64	0.65	0.63
Ride-Hailing CAV with a backup driver present	0.63	0.71	0.63
Ride-Hailing CAV with no backup driver present	0.71	0.75	0.71
Share a CAV (Carpooling)	0.68	0.75	0.70
CAV-based public transport	0.65	0.73	0.67

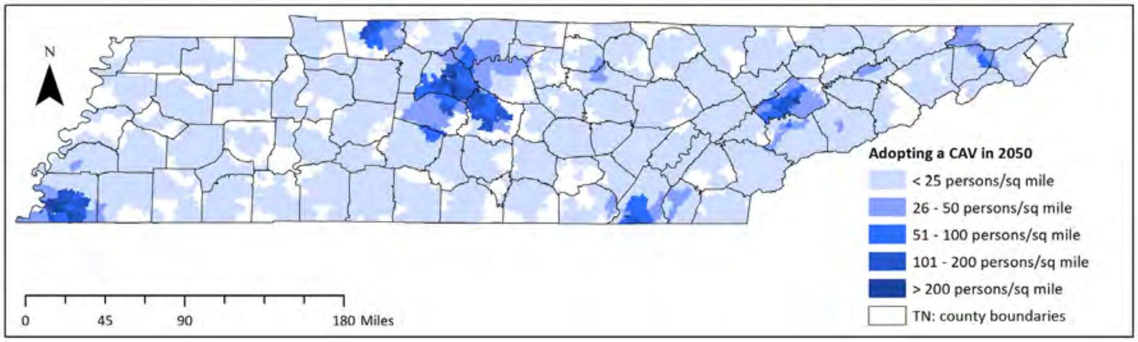
5.3.1 Statewide adoption levels

Figure 5.3 portrays the adoption of privately owned CAVs in the state of Tennessee. Figure 5.3 (a) shows the adoption density (person/sq mile) in 2020 when there is no price reduction, whereas Figure 5.3 (b) and Figure 5.3 (c) present the adoption density under the price reduction of 5% and 20% in 2050, respectively. White spaces in the maps indicate the zip codes with no responses. There would be a low level of adoption in 2020 as the adoption density is less than 25 persons per square mile throughout the state except for a handful of Shelby and Davidson County areas. This could be due to the incipient stage of CAVs (Davidson County close-up shown in Figure 3.4 (a), (b), and (c)). The future adoption scenarios clearly show the impact of price on the adoption rate as the adoption density increases for all four major counties of Tennessee (Davidson, Hamilton, Knox, Shelby). This is probably because of the higher percentage of tech-savvy individuals and individuals aged below 55 years. High earners are willing to pay more for CAVs and receive more exposure to autonomous technologies through media and their peers in these four counties. Overall, the adoption levels are significantly lower in the remaining counties. To further explore the reason, a closer look is taken at the residents interested in adopting but have not adopted yet.

Figure 5.5 shows the Tennessee residents who are interested in adopting privately owned CAVs. These residents show a higher level of interest in CAVs but based on the inputs and information related to CAVs, they could only either choose to adopt or reject the CAVs for these scenarios. From all three figures (Figure 5.5 (a), (b), and (c)), it is evident that there is significantly less impact from the price on the change in density of interested residents. These results highlight the importance of disseminating CAV-related information covering their benefits, solutions for anticipated barriers, and its attractiveness as a social status symbol (Weiss & Fershtman, 1998a). These recommendations are well-supported by the findings of the hybrid choice model, including the impact of social influence, media influence, and attitudes towards CAVs (barriers and benefits). For brevity, the adoption results for CAV-based public transport, carpooling with a CAV, a CAV-based ride-hailing service with and without a backup driver are provided in Appendix B. Overall, privately owned CAV adoption levels were higher than all other four CAV-based travel modes. Interestingly, in 2020, no one was interested in carpooling by CAV, but in 2050, there will be an increase in the number of residents interested in it.



(a)



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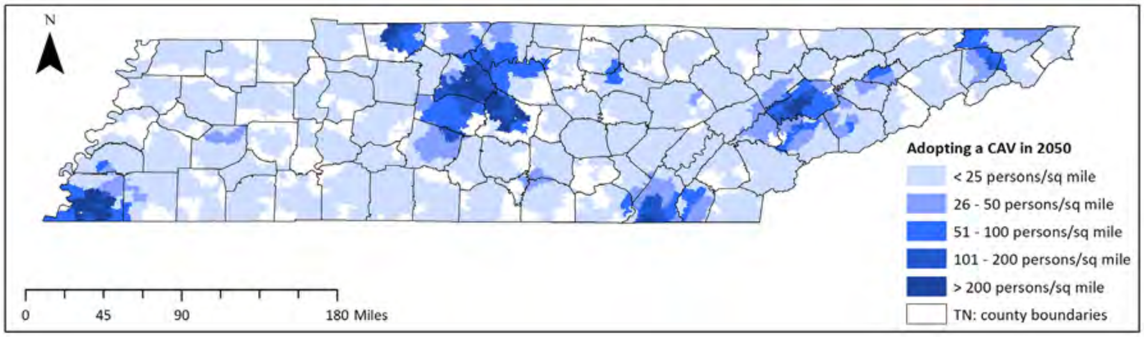
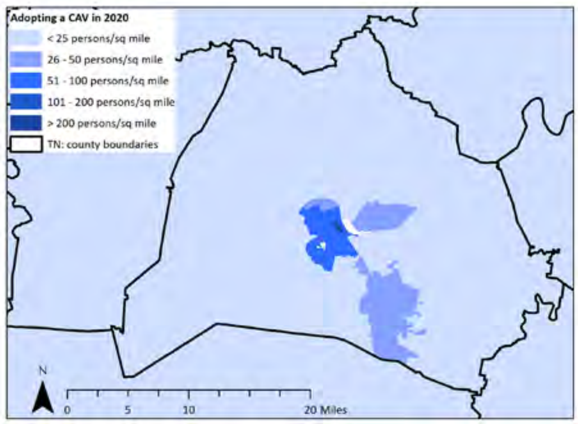


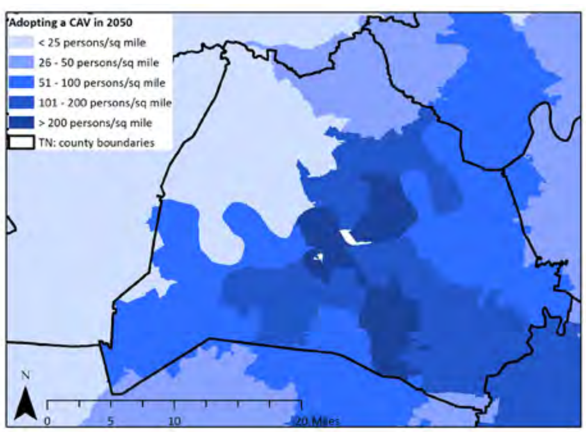
(c)

Figure 5.3

Tennessee residents adopting a personally owned CAV (persons/ sq. mile) (a) 2020 (no price reduction) (b) 2050 (5% price reduction) (c) 2050 (20% price reduction)



(a)



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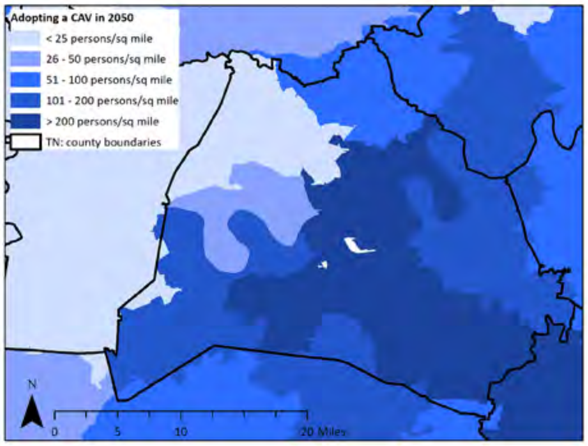
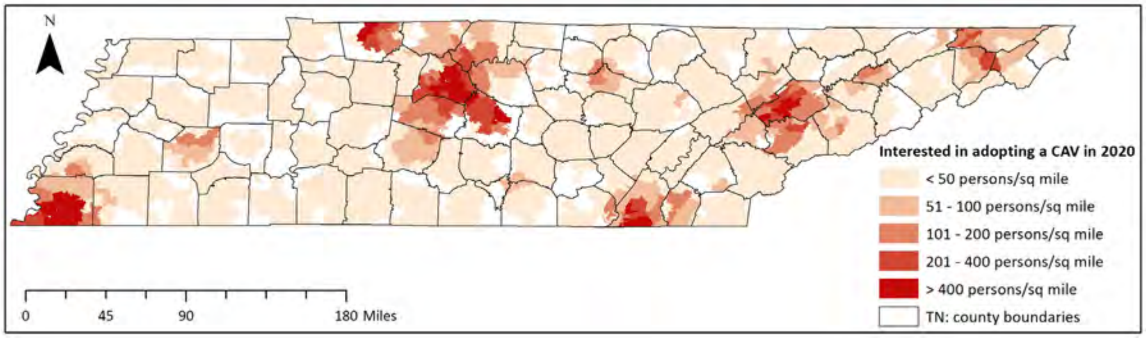


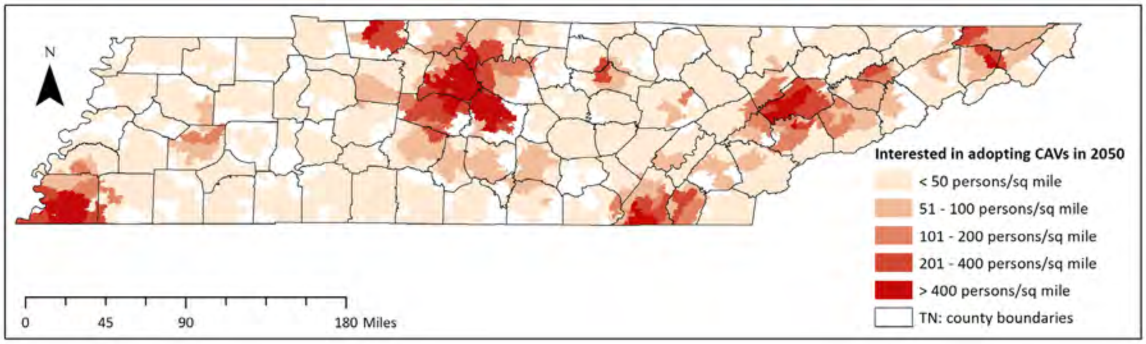
(c)

Figure 5.4

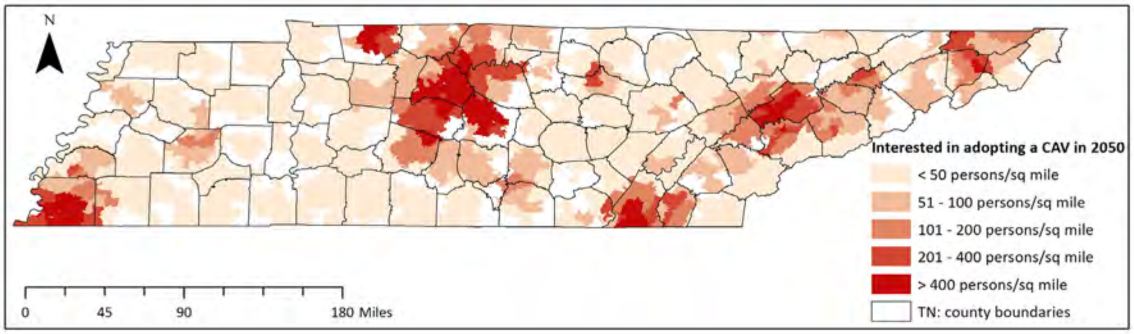
Davidson county residents interested in adopting a personally owned CAV (persons/ sq. mile) (a) 2020 (no price reduction) (b) 2050 (5% price reduction) (c) 2050 (20% price reduction)



(a)



(b)



(c)

Figure 5.5

Tennessee residents interested in adopting a personally owned CAV (persons/ sq. mile) (a) 2020 (no price reduction) (b) 2050 (5% price reduction) (c) 2050 (20% price reduction)

5.3.2 How many CAVs will there be?

Figure 5.6 portrays the number of privately owned CAVs or CAV fleets in the state of Tennessee in the four price reduction scenarios. The CAV fleets in 2020 could increase by up to 9 to 18 times in 2050 under an annual price reduction scenario of 5% and 20%, respectively. The figure also includes a 95% confidence band around the estimates. According to the model, the number of CAV fleets in 2050 could vary from about 500,000 to 900,000 vehicles based on the projected annual price reduction. Among all four major counties, Knox County was forecasted to experience a considerably higher percentage increase in CAV fleet in 2050 from 2020 levels. Among the estimated CAV fleets for four major counties (Figure B.5 in Appendix B), Shelby County would experience the highest number of CAVs in 2050.

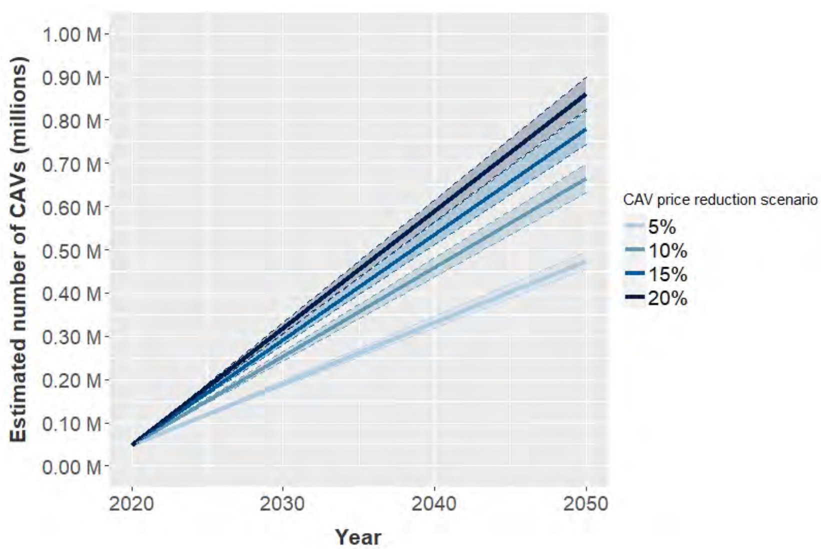


Figure 5.6

Number of privately owned CAVs in 2020 and four price reduction scenarios of 2050 in the state of Tennessee

5.4 Policy Implications and Discussions

Based on the key results identified from both models, this section discusses the policy implications associated with CAV adoption. The majority of the findings align with the existing literature. Some of the findings from this research are novel, especially related to the impact of social network influence and media information. From the adoption estimates, it is evident that a small share of the population currently adopts CAVs in 2020. The adoption rate would get a boost from annual price reduction and the peer-to-peer information effect. Notably, a significant share of the population is interested in adopting, and that population is less sensitive towards the change in the annual price of CAVs. Such a population will decide with or against CAV adoption based on the information they receive from the media and their social network. It also depends on the degree of clarity in the information regarding how to tackle the negative impacts of CAVs.

From the main findings of the HCM framework, we conclude that if individuals are concerned about their social status and influenced form the CAV-related information received from media and their peers, they are more likely to adopt a CAV. This result was consistent with all CAV-based travel modes. Similarly, familiarity with latest smart technologies and willingness to pay a higher amount for autonomous technology also showed favorable results for CAVs. Hence, based on these results and the low adoption rate in a majority of counties, as per the future forecasts, Figure 5.7 portrays the policy framework to boost the CAV adoption rate (especially privately-owned ones) while targeting the residents interested in adopting CAVs that have not adopted yet. As per the policy recommendations, in the initial stages, when CAVs are introduced to the market, automakers and policymakers can focus on the targeted advertisement through social media, consistent with the positive impact of social and media influence on CAV adoption. The target audience could be the individuals up to date with the latest smart technologies (e.g., frequent users of GPS navigation and smart home speakers), potential car buyers, following a flexible work schedule and individuals willing to pay higher for the autonomous technology (in line with the findings of the hybrid choice model). The advertisements should cover the information about the potential benefits of CAVs including increased productivity while traveling, the potential to eliminate human error-related accidents, travel time savings, cost savings (parking and insurance), and increased mobility to the physically disabled population. The advertisements should also include awareness regarding negative aspects of CAVs, such as data privacy safeguards and cybersecurity information. The advertisements can include infographics about autonomous driving operation levels and disengagements. Information can be well supported by including the ability of CAVs to make automated trips to service stations. Being consistent with the findings on social status advertisements can portray CAVs as an attractive vehicle.

After the advertising, once the target individuals buy the CAVs, the government can reduce ownership costs through incentives in vehicle registration discounts, reduced annual renewal costs, and tax rebates. Such initiatives can boost the adoption of CAVs, as demonstrated by the adoption forecast scenarios. CAVs can then be integrated into existing intelligent transportation systems to utilize the existing infrastructure available at TDOT's disposal like SmartWay, which will further revolutionize the travel experience. Once residents adopt a CAV, car dealers in partnership with local administration can offer referral-based incentives where adopters can share their experience over social media and among their peers to encourage the increased adoption. This is supported by the finding of the impact of social influence on CAV adoption. In this direction policies can also be made to put trade-in offers for individuals switching from a conventional car to a CAV.

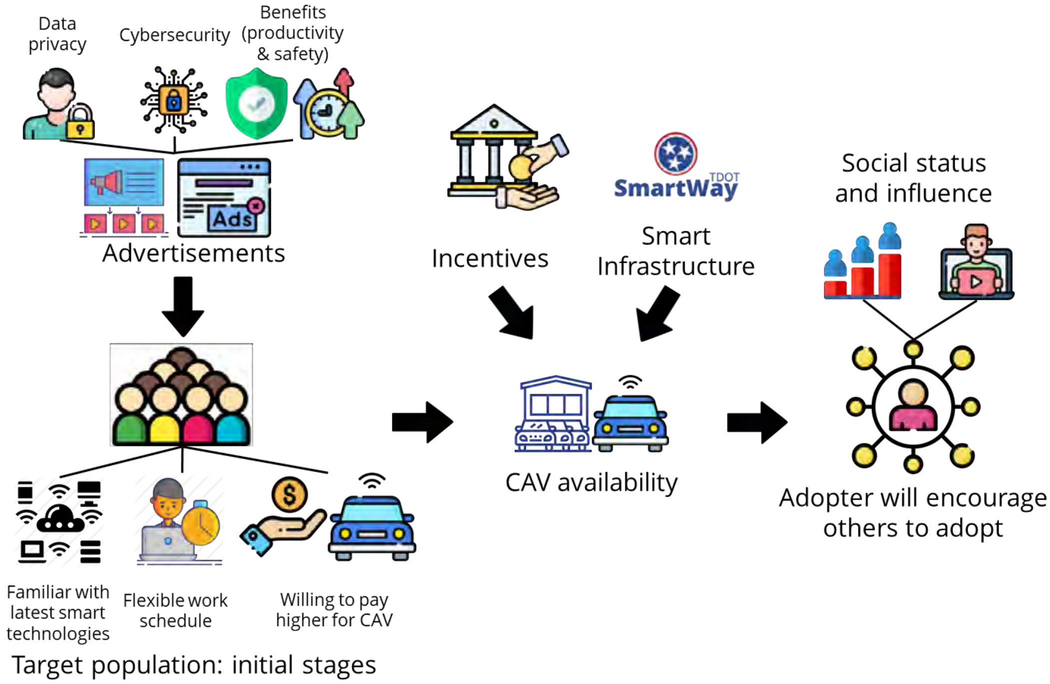


Figure 5.7

Policy framework to boost adoption of privately-owned CAVs in Tennessee based on the results

5.4.1 COVID-19 impact considerations on travel behavior and CAV testing

In addition to the policy implications, the present status of CAVs in terms of their investment, development, testing, and COVID-19 impacts, is also reviewed (portrayed in Figure 5.8). From 2014-18, industries involved in autonomous technology had spent about $80 billion on the research and development of CAVs (McIntyre, 2018). Despite these investments, CAVs are still under development with no near timeline for the launch of level 5 CAVs on the public roads. In addition, from a CAV operation perspective, even a single crash in CAVs gets more attention than conventional vehicle crashes. From late 2020, the COVID-19 pandemic has worsened the adoption timeline for the CAVs due to a halt in their testing. These trends further put a dent in their acceptance.

The social distancing and safety norms in place during the COVID-19 pandemic significantly affected individuals' travel behavior drastically (Abdullah et al., 2020). During the pandemic, private cars emerged as the most preferred travel mode while considering factors like security, infection concern, cleanliness, and social distancing (De Vos, 2020). Consequently, the number of licensed individuals increased, and such individuals were buying new or used conventional cars. On the other side, individuals hesitated to travel in public transit and ride-hailing services (Abdullah et al., 2020). Interestingly, despite the increased use of private cars, there was a significant decrease in the trip frequency of existing private vehicle owners. This was because of the increase in shopping-related trips and the decrease in education and work-related trips. From a distance point of view, short distance trips dominated the long-distance trips as individuals traveled to their nearest supermarkets to complete their grocery-related needs or other essential trips.

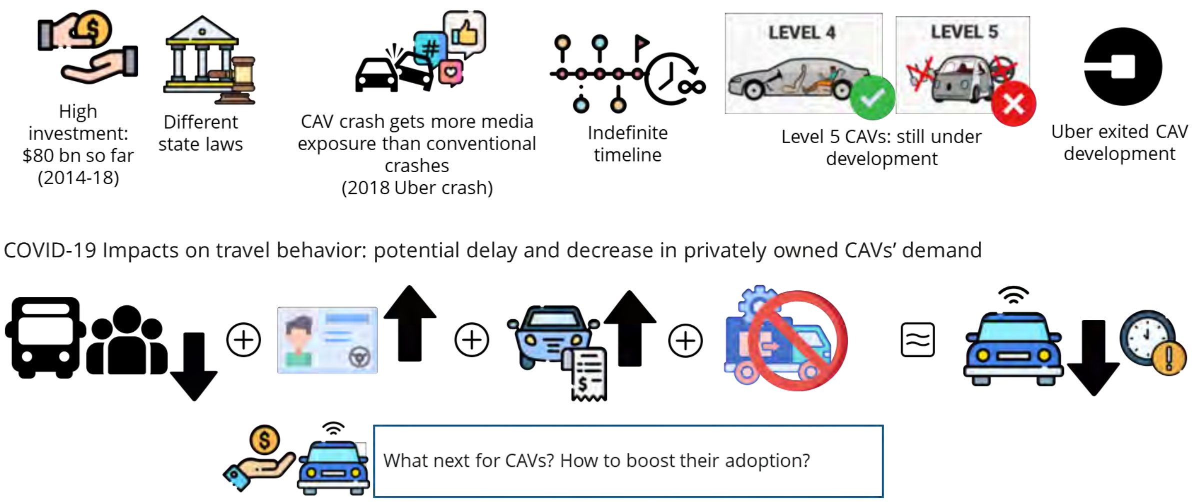


Figure 5.8
Present status of CAV deployment: Investment, crashes, testing and COVID-19 impacts

Although the COVID-19 pandemic has had a detrimental impact on testing CAVs on public roads, it has opened multiple application areas for the CAVs like contactless goods delivery (Kapser et al., 2021; Pani et al., 2020). Such applications have provided early exposure of autonomous technology to the general public, which will assist in altering many negative concerns like privacy, trust, and ease of use. During these times, CAVs could serve as autonomous shuttles for transportation-disadvantaged populations while conforming to social distancing and cleanliness protocols for providing mobility to the nearest supercenters. The increase in the number of new private vehicle owners (De Vos, 2020) and decrease in the frequency of car usage for existing users (Abdullah et al., 2020), presents a unique opportunity. In the initial phases, especially in the COVID-recovery period, CAVs could be introduced under fractional ownership. Under such a business model, individuals would not fully own the vehicle, and cost would be usage-based. The same vehicle, when unattended, could be delegated to others to complete their mobility needs. Such a model would benefit individuals unwilling to pay higher for CAVs (from the key findings of the HCM framework).

Chapter 6 Conclusion

Connected and Autonomous Vehicles (CAVs) could eliminate all human-error-related road crashes. CAVs have the potential to revolutionize the way we travel through increased productivity and travel time savings. However, there are some anticipated negative impacts of CAVs like virus attacks, hacking, data privacy, and cybersecurity. Also, despite the commitments from governments and industries, their adoption is still uncertain. It will be a paradigm shift for the general population to switch to CAVs from conventional vehicles even if CAVs meet their expectations and provide increased utility. The State of Tennessee welcomes CAVs for testing and operation on public roads, making it more important to study the anticipated adoption of CAV in the state. Existing research indicates the importance of peer-to-peer interaction on the adoption of novel technological innovations. However, recent research on CAV adoption fails to capture such impacts. Hence, this project modeled a fusion of agent-based and hybrid choice models that can capture the impact of word-of-mouth (peer-to-peer interaction) and perceptions towards CAV-related positive and negative impacts. The fused use of both models is also capable of forecasting the future market share of CAVs for the state of Tennessee.

An online survey in Tennessee was conducted to collect over 4,602 complete responses through three different survey distribution channels (Amazon Mechanical Turk, market research company panel, social media, and educational institutes in Tennessee). The survey dataset was then used to develop an R-shiny web dashboard to showcase results, generate synthetic population for the entire state, and formulate a hybrid choice model with an ordered framework to capture residents' perceptions and adoption behavior towards CAVs five different CAV-based travel modes: privately owned, carpool, public transport, ride-hailing service with and without the backup human driver. The adoption behavior was measured on three levels: "Fully Adopt, "interested, and "Reject." Then an agent-based model was fused with the hybrid choice model to simulate the impact of peer-to-peer interaction (word-of-mouth) and four different scenarios of annual price reduction of CAVs (5% to 20% with a step size of 5%) on the future adoption of CAVs in Tennessee while utilizing synthetic population and residents' income levels. Finally, county adoption forecasts were provided for all five CAV-based travel modes. Based on the key findings of both models, some key policy implications were identified. In addition, COVID-19 impacts on CAV acceptance based on recent developments in the literature were also explored.

Among the results, in the hybrid choice model, six attitudinal constructs were identified: Social status, Social Influence, CAV Benefits, CAV Barriers, CAV Purchase, and Media Influence. The social status captured the resident's concern towards their image among their peers if they chose to adopt CAVs. Social influence emulated the influence of information received from an individual's social network on their decision to purchase CAVs. CAV Barriers, CAV Benefits, and CAV Purchase represented individuals' concern towards negative, positive, and purchase-related characteristics of CAVs. Finally, Media Influence represented the impact of media advertisements on residents' decision to adopt CAVs. Residents of all ages and income levels were concerned about all six attitudinal constructs, highlighting the importance of peer-to-peer interaction, media advertisements, and factors including positive, negative, and purchase characteristics of CAVs. Individuals who do not receive any CAV-related information from their peers were shown to rely on media advertisements. Individuals willing to pay higher for autonomous technology, following a tech-confident lifestyle, and feeling concerned about all six attitudinal constructs were more likely to adopt all five CAV-based travel modes.

In contrast, elderly and individuals who bought two or more cars in the last ten years were less likely to own CAVs. The agent-based model provided the income-wise proportion of individuals who were likely to change their decision from reject to adopt over time based on the peer-to-peer interaction. The proportion of individuals deciding to adopt CAVs was significantly less than those interested in adopting but have not adopted yet. The adoption forecasts were highest for privately owned CAVs. Four major counties in Tennessee are set to experience high adoption density (person per square mile) in the next 30 years. The annual reduction in the price of CAVs increased the adoption rate by about 18 times according to our modeling. However, the price alone is not enough for the higher adoption levels.

Recommendations

Based on the findings of privately owned CAVs, we propose some policy recommendations to boost their market share in Tennessee. The main recommendation is to focus on a public awareness strategy related to CAVs. As per this strategy, counties identified with low CAV acceptance rates can be targeted in the initial stages. The lessons and impacts of awareness strategies on these counties can then be applied to statewide awareness strategies. At the program level, the awareness strategy might focus on the potential of CAVs in eliminating human-related errors, lower insurance premiums, the ability to multitask while driving, and providing mobility to the disabled. In addition, the focus can be on educating the general public about cybersecurity, data privacy, and safety-related aspects of CAVs. Such efforts will assist in decreasing the resistance associated with CAVs. Such strategies can be run in the pre-introduction stages of CAVs and can be continued based on the exposure to the public. At the project level, awareness strategies can be focused on communicating with the general public while targeting a specific group of residents in the initial studies. Hence, as part of the public awareness strategy, a webpage dedicated to such information can be developed to post the recent updates about CAVs in Tennessee. In addition to websites, social, print, and electronic media can also be utilized to run public awareness. The information can also be disseminated through advertisements and skills embedded in voice-enabled smart assistants. This is well supported by this study's finding of positive relation of social and media influence with residents' intention to adopt a CAV, implying that residents who rely on these will be more swayed by social media and media channels. As per the results of this study, individuals who are updated with the most recent smart technology (like voice-enabled smart assistants), planning to buy a new vehicle, willing to pay higher towards autonomous technology, and follow a flexible work schedule, can be the targeted potential consumers.

During the post-introduction phase of CAVs, the public awareness strategy should be coupled with government incentives to residents interested in adopting CAVs and integrating CAVs into the existing infrastructure facilities. Integrating CAVs with existing infrastructure and intelligent transportation systems like TDOT SmartWay can decrease the operational cost of CAVs and, hence decreasing their price. Finally, a referral-based incentive can encourage adopters to share their experiences among their peers and social media to increase the adoption rate. Such results are expected to assist TDOT in framing policies and plans to boost the adoption of CAVs in Tennessee. The findings also highlight that despite having a positive attitude towards the benefits, purchasing characteristics, and media-related information of CAVs, the elderly population is hesitant to own a CAV. In this direction, targeted advertisements and education campaigns for the elderly population can be run to decrease their resistance towards CAV acceptance. Lessons can be learned from the successful implementation of CAVs in the contactless delivery of goods during the COVID-19 pandemic to eliminate the negative aspects of CAVs. This will ensure higher adoption rates while increasing the proportion of early adopters.

This research also offers some insights of CAVs on travel modes other than personal vehicles while focusing on congestion and safety-related impacts based on the implication identified from residents' perceptions and preferences towards other CAV-based travel modes. The public awareness strategy discussed in the paragraphs above also applies to other CAV-based travel modes as latent factors constructed have a positive relationship with all CAV-based travel modes. The users of existing conventional public transport and ride-hailing services are more likely to be the early adopters of their conventional counterparts; hence targeting such a population through awareness campaigns can increase the wider adoption of these CAV-based travel modes. The campaigns can also target urban residents and residents who do not own a car (motivated by finding frequent private car users with low annual mileage hesitant to adopt CAV-based public transit and ride-hailing service) as regular users of shared mobility-based CAVs. In addition, from the higher adoption rates of CAV-based ride-hailing services without backup human driver than their no human driver counterpart, pilot projects on such services in counties with low CAV adoption rates can help decrease resistance towards CAV acceptance. Existing literature well posits the potential of shared mobility based CAVs in reducing congestion (Kopelias et al., 2020; Metz, 2018), emission (Kopelias et al., 2020; Olia et al., 2016), and crashes (Blanco et al., 2016; Shetty et al., 2021) compared to their conventional counterparts. Hence, wider adoption of these CAV-based travel modes will further contribute to safer, fast, and environment-friendly highways in Tennessee.

The study includes some limitations, and hence results should be considered with caution. Due to computational limitations, we estimated the hybrid choice model sequentially. We applied an agent-based model on the survey dataset, not on the synthetic population, because of the high memory requirement (1TB+) to generate and store the social network for the entire population. Applying the agent-based model to the whole population would have the population's social network instead of survey respondents', resulting in more precise forecasts. Future studies can rectify this limitation.

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Appendices

Appendix A. Hybrid choice model result tables

Table A.1

Hybrid choice model results: SEM structural equation including coefficient (p-value) and significance level (N= 3,221)

Attribute	Description	Social Status	Social Influence	CAV Barriers	CAV Benefits	CAV Purchase	Media Influence
Intercept	Intercept	-0.0028(0.993)	0.353(0.744)	0.945(0.275)	0.634(0.155)	-0.276(0.181)	0.7(0.194)
Age	18 to 35 years	1.62(0.0)***	1.39(0.001)***	--	0.809(0.0)***	0.336(0.045)*	0.814(0.001)***
	35 to 54 years	0.911(0.0)***	1.14(0.008)**	--	1.14(0.002)**	0.741(0.0)***	0.713(0.001)***
	more than 54 years	-0.537(0.029)*	--	--	0.687(0.004)**	0.647(0.002)**	1.17(0.0)***
Gender	Male (base: Female)	-0.388(0.046)*	--	1.01(0.0)***	--	1.15(0.0)***	-0.533(0.0)***
Ethnicity	White	-0.449(0.018)*	--	--	--	--	--
	African American	--	--	--	--	--	--
	Others	-0.693(0.005)**	--	--	--	--	--
Marital status	Single	-0.387(0.03)*	--	--	--	--	--
	Married	-0.256(0.097)#	--	--	--	--	--
	Separated, divorced, widowed	--	--	--	--	--	--
Educational Attainment	High school or below	--	-0.729(0.054)#	-0.656(0.002)**	--	--	--
	Some College	-0.422(0.014)*	-0.819(0.013)*	--	--	--	--
	College Graduate	--	--	--	--	--	--
	Master's, doctoral or professional degree	-0.421(0.033)*	--	--	--	--	--
Personal annual income	less than $35,000	0.637(0.006)**	1.03(0.047)*	--	1.42(0.021)*	0.825(0.001)***	0.76(0.002)**
	$35,000-$75,000	0.573(0.002)**	--	--	1.1(0.002)**	0.631(0.001)***	0.884(0.0)***
	more than $75,000	0.787(0.0)***	0.683(0.084)#	--	--	--	1.06(0.0)***
Frequency of listening to Radio	Frequent (everyday)	-0.375(0.097)#	--	--	--	-0.336(0.094)#	--
	Infrequent (once a week to a year)	-0.947(0.0)***	--	--	--	--	--

Attribute	Description	Social Status	Social Influence	CAV Barriers	CAV Benefits	CAV Purchase	Media Influence
	Never	--	--	--	--	-1.05(0.006)**	--
Frequency of watching TV	Frequent (everyday)	--	--	--	--	--	-0.867(0.004)**
	Infrequent (once a week to a year)	--	-0.949(0.002)**	--	--	-1.24(0.0)***	--
	Never	-1.39(0.018)*	--	--	--		--
Frequency of using smart home appliances like Amazon Alexa	Frequent (everyday)	--	--	--	--	-0.553(0.005)**	-0.431(0.05)*
	Infrequent (once a week to a year)	--	--	--	--	-0.734(0.0)***	--
	Never	-1.11(0.0)***	-0.939(0.022)*	--	-0.417(0.078)#	--	0.33(0.082)#
Household location	Urban	--	--	--	--	--	-0.414(0.026)*
	Semi-urban	-0.572(0.002)**	--	--	--	--	--
	Rural	-0.551(0.004)**	--	--	--	--	--
Household members	two or less	-0.604(0.001)***	--	--	-0.513(0.057)#	-0.836(0.0)***	--
	three or more	-0.399(0.048)*	--	--		-0.44(0.004)**	--
Annual household income	less than $35,000	0.425(0.07)#	0.822(0.042)*	--	0.64(0.031)*		1.01(0.0)***
	$35,000-$100,000	0.71(0.001)***	0.891(0.045)*	--	0.692(0.002)**	0.912(0.0)***	0.841(0.0)***
	more than $100,000	0.863(0.0)***	--	--	1.3(0.011)*	0.641(0.007)**	0.847(0.0)***
Household Cars	one and zero	--	--	--	--	-0.298(0.06)#	--
	two	--	--	--	--	-0.878(0.0)***	--
	three or more	--	--	--	--		--
New Cars purchased in last 10 years	one and zero	--	--	--	--	-0.87(0.0)***	--
	two	--	--	--	--	--	--
	three or more	--	--	--	--	--	--
Frequency of purchasing a conventional car	Once a year to every 2-3 years	--	--	--	--	--	--
	Once every 5 to 10 years	--	--	--	--	0.349(0.038)*	--
	Once every 15 to 20 years	--	--	--	--	1.23(0.0)***	--
Willingness to pay towards purchasing a conventional car	less than $15,000	--	--	--	--	0.595(0.001)***	--
	$15,000-$30,000	--	--	--	--	1.07(0.0)***	--
	more than $30,000	--	--	--	--	--	--

Attribute	Description	Social Status	Social Influence	CAV Barriers	CAV Benefits	CAV Purchase	Media Influence
Working from home: frequency	Frequent (everyday)	-0.358(0.075)#	--	--	--	--	--
	Infrequent (once a week to a year)	-0.479(0.012)*	--	--	--	-0.903(0.0)***	--
	Never	--	--	--	--	-0.399(0.034)*	--
Flexibility in work schedule	Flexible	--	--	--	--	-0.502(0.007)**	--
	Somewhat flexible	-0.339(0.061)#	--	--	--	-0.712(0.0)***	--
	Inflexible	-0.41(0.024)*	--	--	--	--	--
Annual mileage	less than 5,000 miles	--	--	--	--	--	--
	more than 5,000 miles	--	--	--	--	--	--
Frequency of using private car for daily commute	Frequent (everyday)	--	--	--	--	0.393(0.087)#	--
	Infrequent (once a week to a year)	--	--	--	--	-1.17(0.0)***	--
	Never	--	--	--	--	-0.496(0.048)*	--
Frequency of using public transport for daily commute	Frequent (everyday)	--	--	--	--	-1.07(0.002)**	--
	Infrequent (once a week to a year)	--	--	--	--	-0.813(0.022)*	--
	Never	--	--	--	--	0.601(0.026)*	--
Frequency of using ride sharing services for daily commute	Frequent (everyday)	--	--	--	--		--
	Infrequent (once a week to a year)	--	--	--	--	-0.89(0.002)**	--
	Never	--	--	--	--		--
Frequency of using ride hailing services for daily commute	Frequent (everyday)	--	--	--	--	-1.17(0.001)***	--
	Infrequent (once a week to a year)	--	--	--	--		--
	Never	--	--	--	--		--
Willingness to pay towards adding autonomous technology in an existing conventional car	less than $2,500	--	--	--	--	0.672(0.0)***	--
	$2,500 to $7,500	--	--	--	--	0.354(0.043)*	--
	more than $7,500	--	--	--	--	0.698(0.001)***	--
Willingness to pay more	$0	--	--	--	--	--	--
	$0 to $300	--	--	--	--	0.728(0.0)***	--

Attribute	Description	Social Status	Social Influence	CAV Barriers	CAV Benefits	CAV Purchase	Media Influence
towards the annual maintenance of a CAV than a conventional car	more than $300	--	--	--	--	0.713(0.0)***	--
Number of peers having knowledge about cars	zero	-0.612(0.004)**	-3.06(0.0)***	--	--	--	0.57(0.006)**
	1 to 2 peers	--		--	--	-0.778(0.0)***	--
	more than 2 peers	--	1.69(0.001)***	--	--	--	-0.667(0.001)***
Frequency of communication with social ties developed at work	Frequent (2-3 times a week to daily)	-0.272(0.087)#	0.775(0.074)#	--	--	--	--
	Sometimes (every couple of weeks to month)	-0.533(0.005)**		--	--	-0.772(0.0)***	--
	Infrequent (once per month to every few months)	--	-1.36(0.001)***	0.424(0.03)*	--		--
Survey channel	Amazon Mechanical Turk (Mturk)	-0.594(0.002)**			--		--
	Social media and educational institutes	-1.39(0.0)***		0.696(0.089)#	--	-0.592(0.037)*	--
	Panel from market research company	0.985(0.0)***	-0.933(0.029)*	-0.668(0.004)**	--	-0.996(0.0)***	--
Any kind of disability which undermines driving	Yes (base: No)	-0.849(0.005)**	--	--	--	0.819(0.023)*	--
Number of peers in social network		4.77(0.0)***	1.67(0.004)**	--	--	--	-1.3(0.0)***
Familiarity with CAVs	Yes (base: No)	-0.981(0.0)***	--	1.72(0.0)***	--	1.35(0.0)***	--
Willing to pay more if CAV drive themselves to service stations	Yes (base: No)	--	--	--	--	0.666(0.012)*	--

Significance levels: -- not significant, #0.10, *0.05, **0.01, ***0.001

Table A.2

Hybrid choice model results: Goodness of fit measures (N= 3,221)

Measure	Value
Initial log-likelihood	-267,603.50
Final log-likelihood	-140,811.70
Likelihood ratio test	253,583.50
Rho-square	0.474
Adjusted Rho-square-bar	0.472
Akaike Information Criterion	282,333.50
Bayesian Information Criterion	284,491.00

Table A.3

Hybrid choice model results: SEM measurement equation including coefficient (p-value) and significance level (N= 3,221)

Base attribute	Attribute	Coefficient	Social Status	Social Influence	CAV Barriers	CAV Benefits	CAV Purchase	Media Influence
ATT19: LoseTies	*ATT04: PersonalImage*	*Intercept*	--	--	--	--	--	--
		Beta	1.21(0.0)***	--	--	--	--	--
	ATT25: StatusImprove	*Intercept*	--	--	--	--	--	--
		Beta	2.53(0.0)***	--	--	--	--	--
ATT11: NonWorkSocialNetImp	*ATT06: FriendRel*	*Intercept*	--	--	--	--	--	--
		Beta	--	1.12(0.0)***	--	--	--	--
	ATT10: WorkSocialNetImp	*Intercept*	--	--	--	--	--	--
		Beta	--	1.82(0.0)***	--	--	--	--
ATT17: FullControl	*ATT12: PoorInternet*	*Intercept*	--	--	--	--	--	--
		Beta	--	--	0.94(0.0)***	--	--	--
	ATT13: TakeOver	*Intercept*	--	--	--	--	--	--
		Beta	--	--	0.89(0.0)***	--	--	--
	ATT14: SystemFailure	*Intercept*	--	--	--	--	--	--
		Beta	--	--	1.21(0.0)***	--	--	--
	ATT15: VirusAttack	*Intercept*	--	--	--	--	--	--
		Beta	--	--	1.06(0.0)***	--	--	--
	ATT16: LessAgility	*Intercept*	--	--	1.62(0.006)**	--	--	--
		Beta	--	--	0.506(0.0)***	--	--	--
	ATT22: AnnMaint	*Intercept*	--	--	1.16(0.004)**	--	--	--
		Beta	--	--	0.347(0.0)***	--	--	--
	ATT18: LessSafe	*Intercept*	--	--	--	--	--	--
		Beta	--	--	0.911(0.0)***	--	--	--
ATT21: Green	*ATT24: Multitask*	*Intercept*	--	--	--	--	--	--
		Beta	--	--	--	--	--	--
	ATT26: LessInsPrem	*Intercept*	--	--	--	--	--	--
		Beta	--	--	--	--	--	--
	ATT27: SmartPark	*Intercept*	--	--	--	--	--	--
		Beta	--	--	--	--	--	--
	ATT20: TSP	*Intercept*	--	--	--	--	--	--
		Beta	--	--	--	--	--	--
	ATT23: MobForDisabled	*Intercept*	--	--	--	--	--	--

Base attribute	Attribute	Coefficient	Social Status	Social Influence	CAV Barriers	CAV Benefits	CAV Purchase	Media Influence
		Beta	--	--	--	--	--	--
ATT02: CarQuality	*ATT01: CarPrice*	*Intercept*	--	--	--	--	--	--
		Beta	--	--	--	--	0.548(0.0)***	--
	ATT05: ServiceStationTrips	*Intercept*	--	--	--	--	--	--
		Beta	--	--	--	--	0.316(0.0)***	--
	ATT03: Environment	*Intercept*	--	--	--	--	--	--
		Beta	--	--	--	--	0.097(0.004)**	--
ATT08: DealerRel	*ATT07: AdvtRel*	*Intercept*	--	--	--	--	--	--
		Beta	--	--	--	--	--	-1.18(0.0)***

Significance levels: **-- not significant, #0.10, *0.05, **0.01, ***0.001**

Table A.4

Hybrid choice model results: Ordinal logit with latent variables for each CAV-based travel mode including coefficient (p-value) and significance level (N= 3,221)

Attribute	Description	Own a CAV	Ride-Hailing CAV with a backup driver present	Ride-Hailing CAV with no backup driver present	Share a CAV (Carpooling)	CAV-based public transport
Age (base: 18 to 35 years)	35 to 54 years	-0.163(0.091)#	--	--	--	--
	more than 54 years	-0.285(0.022)*	--	--	--	--
Gender (base: Female)	Male	--	0.549(0.0)***	--	0.216(0.038)*	0.558(0.0)***
Race (base: others)	White	--	--	--	--	-0.309(0.032)*
	African American	--	--	--	--	-0.374(0.028)*
Marital status (base: Separated, divorced, widowed)	Single	--	--	--	0.211(0.026)*	0.364(0.019)*
	Married	--	--	--	--	0.362(0.014)*
Educational Attainment (base: High school or below)	Some College	--	--	--	--	--
	College Graduate	--	-0.243(0.02)*	--	--	--
	Master's, doctoral or professional degree	--	--	--	--	--
Frequency of listening to Radio (base: Never)	Frequent (everyday)	--	-0.173(0.075)#	--	--	--
	Infrequent (once a week to a year)	--	--	--	--	--
Frequency of using smart home appliances like Amazon Alexa (base: Never)	Frequent (everyday)	0.637(0.0)***	0.418(0.005)**	0.372(0.001)***	--	0.333(0.004)**
	Infrequent (once a week to a year)	0.359(0.001)***	0.302(0.027)*	--	--	--
Household location (base: Rural)	Urban		0.289(0.01)**	0.291(0.002)**	--	0.312(0.003)**
	Semi-urban		--	--	--	--
Annual household income (base: less than $35,000)	$35,000-$100,000	-0.396(0.0)***	--	--	--	-0.261(0.005)**
	more than $100,000		--	--	--	--
Number of new conventional cars purchased (last ten years) (base: one and zero)	two		--	--	--	--
	three or more		--	--	-0.203(0.047)*	
Number of used conventional cars	one	-0.273(0.008)**	--	--	--	--
	two or more	-0.322(0.001)***	-0.223(0.024)*	--	--	--

Attribute	Description	Own a CAV	Ride-Hailing CAV with a backup driver present	Ride-Hailing CAV with no backup driver present	Share a CAV (Carpooling)	CAV-based public transport
purchased (last ten years) (base: zero)						
Frequency of purchasing a conventional car (base: Once every 15 to 20 years)	Once a year to every 2-3 years	--	0.19(0.083)#	--	0.236(0.028)*	--
	Once every 5 to 10 years	--	--	--	--	--
Working from home: frequency (base: Never)	Frequent (everyday)	--	--	--	0.256(0.006)**	--
	Infrequent (once a week to a year)	--	--	--	--	--
Flexibility in work schedule (base: Inflexible)	Flexible	0.2(0.015)*	--	--	--	--
	Somewhat flexible	--	--	--	--	--
Frequency of using GPS Navigation (base: Never)	Frequent (everyday)	0.825(0.0)***	--	0.28(0.008)**	0.799(0.0)***	
	Infrequent (once a week to a year)	0.564(0.0)***	--	--	0.624(0.001)***	
Annual mileage (base: less than 5,000 miles)	more than 5,000 miles	--	--	-0.272(0.001)***	-0.275(0.003)**	-0.245(0.006)**
Frequency of using private car for daily commute (base: Never)	Frequent (everyday)	--	-0.317(0.029)*	--	-0.289(0.044)*	--
	Infrequent (once a week to a year)	--	--	--	--	--
Frequency of using public transport for daily commute (base: Never)	Frequent (everyday)	--	--	--	0.342(0.032)*	0.659(0.0)***
	Infrequent (once a week to a year)	--	--	--	--	0.821(0.0)***
Frequency of using ride sharing services for daily commute (base: Never)	Frequent (everyday)	--	0.567(0.002)**	--	--	--
	Infrequent (once a week to a year)	--	0.413(0.014)*	--	--	--
Willingness to pay towards adding autonomous technology in an existing conventional car (base: less than $2,500)	$2,500 to $7,500	1.439(0.0)***	0.649(0.0)***	0.772(0.0)***	0.841(0.0)***	0.679(0.0)***
	more than $7,500	1.521(0.0)***	1.0(0.0)***	0.951(0.0)***	0.954(0.0)***	0.779(0.0)***
Willingness to pay more towards the annual maintenance of a CAV	$0 to $300	--	--	--	--	--
	more than $300	--	--	--	--	0.301(0.002)**

Attribute	Description	Own a CAV	Ride-Hailing CAV with a backup driver present	Ride-Hailing CAV with no backup driver present	Share a CAV (Carpooling)	CAV-based public transport
than a conventional car (annually): (base: $0)						
Frequency of communication with social ties developed at work (base: Infrequent i.e., once per month to every few months)	Frequent (2-3 times a week to daily)	--	--	-0.212(0.029)*	--	--
	Sometimes (every couple of weeks to month)	--	0.3(0.009)**	--	0.403(0.0)***	--
Survey channel (base: Panel from market research company)	Amazon Mechanical Turk (MTurk)	0.244(0.018)*	--	--	--	--
	Social media and educational institutes	--	--	--	--	--
Planning to sell or purchase a car (next three years) (base: No)	Yes	0.399(0.0)***	--	--	--	--
Past involvement in vehicle crash(s) (base: No)	Yes	--	--	-0.201(0.013)*	--	--
Latent Variable	Social Status	1.683(0.0)***	3.413(0.0)***	2.233(0.0)***	3.149(0.0)***	2.064(0.0)***
	Social Influence	2.209(0.0)***	1.54(0.001)***	1.862(0.0)***	2.286(0.0)***	1.97(0.0)***
	CAV Barriers	--	0.877(0.005)**	--	--	1.102(0.0)***
	CAV Benefits	--	0.857(0.003)**	1.104(0.0)***	0.983(0.0)***	0.629(0.016)*
	CAV Purchase	3.398(0.0)***	2.507(0.0)***	2.264(0.0)***	2.077(0.0)***	1.885(0.0)***
	Media Influence	--	2.185(0.002)**	1.71(0.002)**	1.964(0.0)***	1.436(0.024)*
Threshold	Threshold 1	7.35(0.0)***	8.02(0.0)***	6.01(0.0)***	7.79(0.0)***	6.73(0.0)***
	Threshold 2	9.52(0.0)***	10.0(0.0)***	8.04(0.0)***	9.97(0.0)***	8.71(0.0)***

Significance levels: -- not significant, #0.10, *0.05, **0.01, ***0.001

Table A.5
Hybrid choice model results: Marginal effects for privately owned CAVs (N= 3,221)

Attribute	Description	Reject	Interested	Fully adopt
Age (base: 18 to 35 years)	35 to 54 years	0.038	-0.028	-0.01
	more than 54 years	0.066	-0.05	-0.017
Frequency of using smart home appliances like Amazon Alexa (base: Never)	Frequent (everyday)	-0.154	0.109	0.046
	Infrequent (once a week to a year)	-0.086	0.062	0.024
Annual household income (base: less than $35,000)	$35,000-$100,000	**0.093**	**-0.069**	**-0.024**
	more than $100,000	--	--	--
Number of used conventional cars purchased (last ten years) (base: zero)	one	0.063	-0.047	-0.016
	two or more	0.075	-0.056	-0.019
Flexibility in work schedule (base: Inflexible)	Flexible	-0.047	0.035	0.012
	Somewhat flexible	--	--	--
Frequency of using GPS Navigation (base: Never)	Frequent (everyday)	-0.201	0.137	0.064
	Infrequent (once a week to a year)	-0.129	0.097	0.032
Willingness to pay towards adding autonomous technology in an existing conventional car (base: less than $2,500)	$2,500 to $7,500	-0.342	0.224	0.118
	more than $7,500	-0.362	0.227	0.135
Survey channel (base: Panel from market research company)	Amazon Mechanical Turk (MTurk)	-0.059	0.042	0.016
	Social media and educational institutes	--	--	--
Planning to sell or purchase a car (next three years) (base: No)	Yes	-0.093	0.069	0.024
Latent variables	Social Status	-0.397	0.294	0.104
	Social Influence	-0.521	0.385	0.136
	CAV Purchase	**-0.802**	**0.593**	**0.209**

Note: **Bold** values indicate maximum and minimum values

Table A.6

Hybrid choice model results: Marginal effects for carpooling/sharing a CAV (N= 3,221)

Attribute	Description	Reject	Interested	Fully adopt
Gender (base: Female)	Male	-0.035	0.029	0.006
Number of new conventional cars purchased (last ten years) (base: one and zero)	two			
	three or more	0.032	-0.027	-0.005
Frequency of purchasing a conventional car (base: Once every 15 to 20 years)	Once a year to every 2-3 years	-0.04	0.033	0.007
	Once every 5 to 10 years			
Working from home: frequency (base: Never)	Frequent (everyday)	-0.042	0.035	0.007
	Infrequent (once a week to a year)			
Frequency of using GPS Navigation (base: Never)	Frequent (everyday)	-0.147	0.119	0.028
	Infrequent (once a week to a year)	-0.095	0.079	0.016
Annual mileage (base: less than 5,000 miles)	more than 5,000 miles	0.045	-0.037	-0.008
Frequency of using private car for daily commute (base: Never)	Frequent (everyday)	**0.049**	**-0.041**	**-0.009**
	Infrequent (once a week to a year)			
Frequency of using public transport for daily commute (base: Never)	Frequent (everyday)	-0.06	0.049	0.011
	Infrequent (once a week to a year)			
Willingness to pay towards adding autonomous technology in an existing conventional car (base: less than $2,500)	$2,500 to $7,500	-0.149	0.121	0.027
	more than $7,500	-0.175	0.141	0.034
Frequency of communication with social ties developed at work (base: Infrequent i.e., once per month to every few months)	Frequent (2-3 times a week to daily)			
	Sometimes (every couple of weeks to month)	-0.07	0.057	0.012
Latent variables	Social Status	-0.508	0.422	0.086
	Social Influence	**-0.369**	**0.306**	**0.062**
	CAV Benefits	-0.159	0.132	0.027
	CAV Purchase	-0.335	0.278	0.057
	Media Influence	-0.317	0.263	0.054

Note: **Bold** values indicate maximum and minimum values

Table A.7

Hybrid choice model results: Marginal effects for CAV-based public transport (N= 3,221)

Attribute	Description	Reject	Interested	Fully adopt
Gender (base: Female)	Male	-0.103	0.080	0.023
Race (base: others)	White	0.058	-0.045	**-0.013**
	African American	0.063	-0.050	-0.013
Marital status (base: Separated, divorced, widowed)	Single	-0.068	**0.053**	0.016
	Married	-0.065	0.051	0.014
Frequency of using smart home appliances like Amazon Alexa (base: Never)	Frequent (everyday)	**-0.063**	0.049	0.014
	Infrequent (once a week to a year)	--	--	--
Household location (base: Rural)	Urban	-0.059	0.045	0.013
	Semi-urban	--	--	--
Annual household income (base: less than $35,000)	$35,000-$100,000	0.047	-0.037	-0.010
	more than $100,000	--	--	--
Annual mileage (base: less than 5,000 miles)	more than 5,000 miles	0.045	-0.035	-0.01
Frequency of using public transport for daily commute (base: Never)	Frequent (everyday)	-0.135	0.101	0.034
	Infrequent (once a week to a year)	-0.174	0.128	0.046
Willingness to pay towards adding autonomous technology in an existing conventional car (base: less than $2,500)	$2,500 to $7,500	-0.131	0.100	0.031
	more than $7,500	-0.155	0.117	0.038
Willingness to pay more towards the annual maintenance of a CAV than a conventional car (annually): (base: $0)	$0 to $300	--	--	--
	more than $300	-0.056	0.044	0.013
Latent variables	Social Status	**-0.374**	**0.292**	**0.082**
	Social Influence	-0.357	0.279	0.078
	CAV Barriers	-0.200	0.156	0.044
	CAV Benefits	-0.114	0.089	0.025
	CAV Purchase	-0.341	0.266	0.075
	Media Influence	-0.260	0.203	0.057

Note: **Bold** values indicate maximum and minimum values

Table A.8

Hybrid choice model results: Marginal effects for CAV ride hailing service with backup driver present (N= 3,221)

Attribute	Description	Reject	Interested	Fully adopt
Gender (base: Female)	Male	-0.081	0.066	0.016
Educational Attainment (base: High school or below)	Some College			
	College Graduate	0.034	-0.028	-0.006

Attribute	Description	Reject	Interested	Fully adopt
	Master's, doctoral or professional degree	--	--	--
Frequency of listening to Radio (base: Never)	Frequent (everyday)	0.025	-0.020	-0.005
	Infrequent (once a week to a year)	--	--	--
Frequency of using smart home appliances like Amazon Alexa (base: Never)	Frequent (everyday)	-0.064	0.052	0.013
	Infrequent (once a week to a year)	-0.046	0.037	0.009
Household location (base: Rural)	Urban	-0.043	0.035	0.008
	Semi-urban	--	--	--
Number of used conventional cars purchased (last ten years) (base: zero)	one	--	--	--
	two or more	0.032	-0.026	-0.006
Frequency of purchasing a conventional car (base: Once every 15 to 20 years)	Once a year to every 2-3 years	-0.028	0.023	0.005
	Once every 5 to 10 years	--	--	--
Frequency of using private car for daily commute (base: Never)	Frequent (everyday)	**0.049**	**-0.039**	**-0.010**
	Infrequent (once a week to a year)	--	--	--
Frequency of using ride sharing services for daily commute (base: Never)	Frequent (everyday)	-0.095	0.075	0.020
	Infrequent (once a week to a year)	-0.067	0.053	0.014
Willingness to pay towards adding autonomous technology in an existing conventional car (base: less than $2,500)	$2,500 to $7,500	-0.101	0.081	0.020
	more than $7,500	-0.168	0.132	0.036
Frequency of communication with social ties developed at work (base: Infrequent i.e., once per month to every few months)	Frequent (2-3 times a week to daily)	--	--	--
	Sometimes (every couple of weeks to month)	-0.046	0.037	0.009
Latent variables	Social Status	**-0.492**	**0.398**	**0.094**
	Social Influence	-0.222	0.180	0.042
	CAV Barriers	-0.126	0.102	0.024
	CAV Benefits	-0.124	0.100	0.024
	CAV Purchase	-0.361	0.292	0.069
	Media Influence	-0.315	0.255	0.06

Note: **Bold** values indicate maximum and minimum values

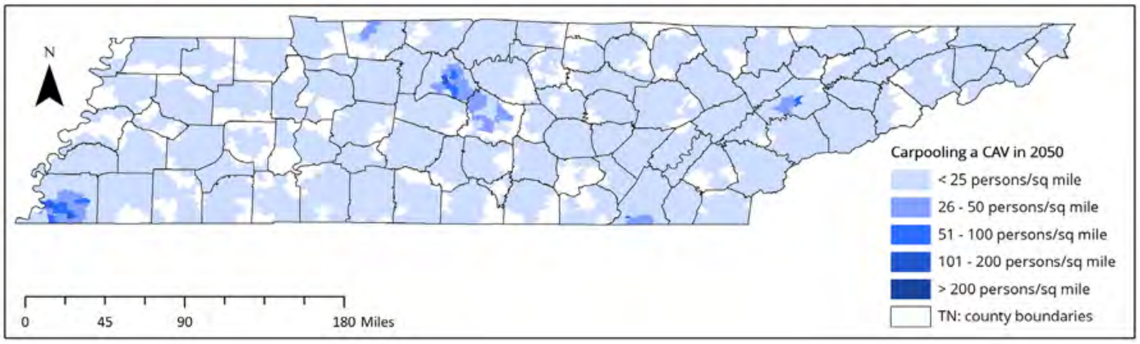
Table A.9

Hybrid choice model results: Marginal effects for CAV ride hailing service with no backup driver present (N= 3,221)

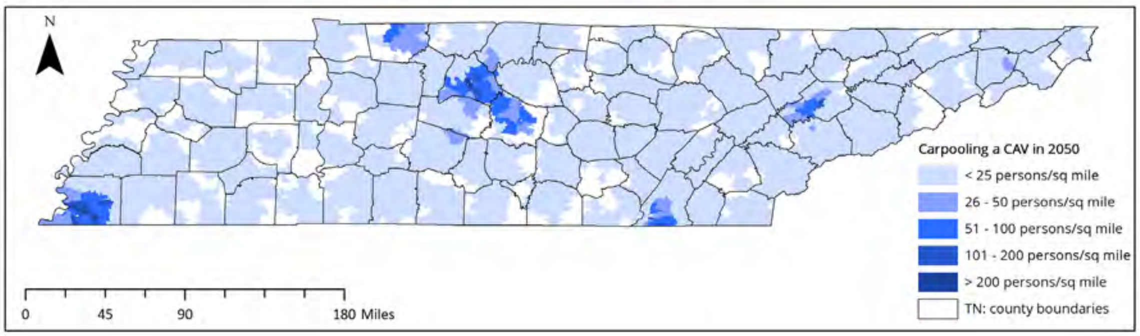
Attribute	Description	Reject	Interested	Fully adopt
Frequency of using smart home appliances like Amazon Alexa (base: Never)	Frequent (everyday)	-0.080	0.060	0.020
	Infrequent (once a week to a year)	--	--	--
Household location (base: Rural)	Urban	-0.062	0.047	0.015
	Semi-urban			
Frequency of using GPS Navigation (base: Never)	Frequent (everyday)	-0.061	0.045	0.015
	Infrequent (once a week to a year)	--	--	--
Annual mileage: more than 5,000 miles (base: less than 5,000 miles)		**0.057**	**-0.043**	**-0.014**
Willingness to pay towards adding autonomous technology in an existing conventional car (base: less than $2,500)	$2,500 to $7,500	-0.169	0.124	0.045
	more than $7,500	-0.213	0.153	0.06
Frequency of communication with social ties developed at work (base: Infrequent i.e., once per month to every few months)	Frequent (2-3 times a week to daily)	0.044	-0.034	-0.011
	Sometimes (every couple of weeks to month)	--	--	--
Past involvement in vehicle crash(s) (base: No)	Yes	0.042	-0.032	-0.010
Latent variables	Social Status	-0.466	0.354	0.112
	Social Influence	-0.389	0.295	0.093
	CAV Benefits	-0.231	0.175	0.055
	CAV Purchase	**-0.473**	**0.359**	**0.114**
	Media Influence	-0.357	0.271	0.086

Note: **Bold** values indicate maximum and minimum values

Appendix B. Statewide adoption maps

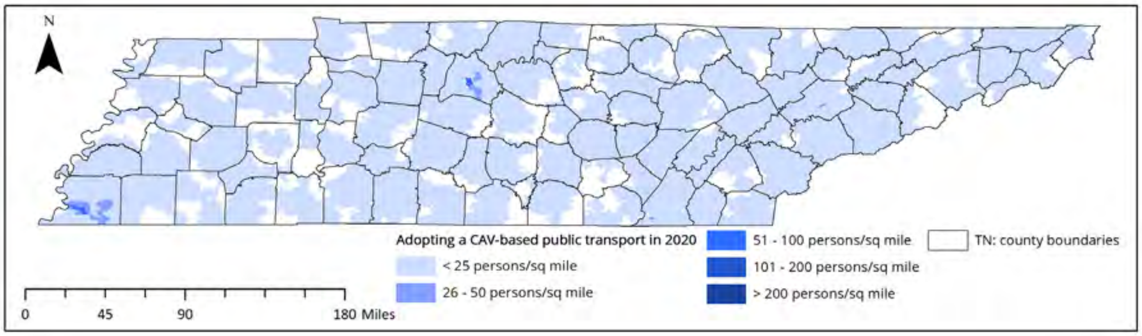


(a)

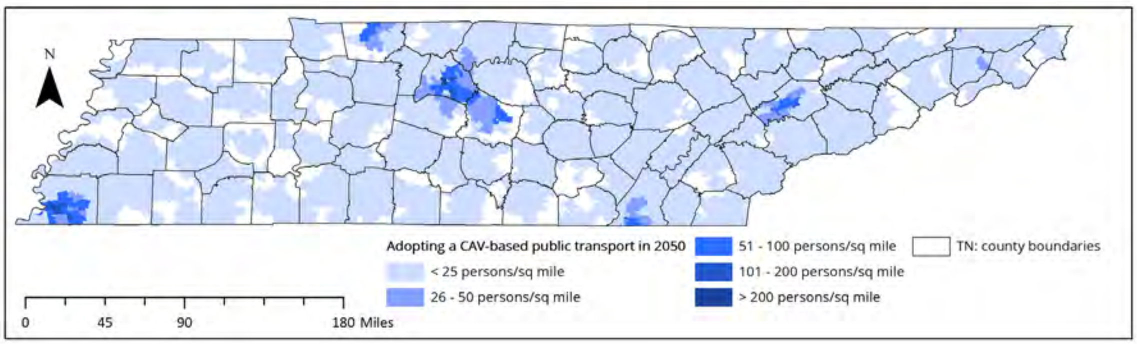


(b)

Figure B.1
Tennessee residents carpooling a CAV (persons/ sq. mile) (a) 2050 (5% price reduction) (b) 2050 (20% price reduction)



(a)



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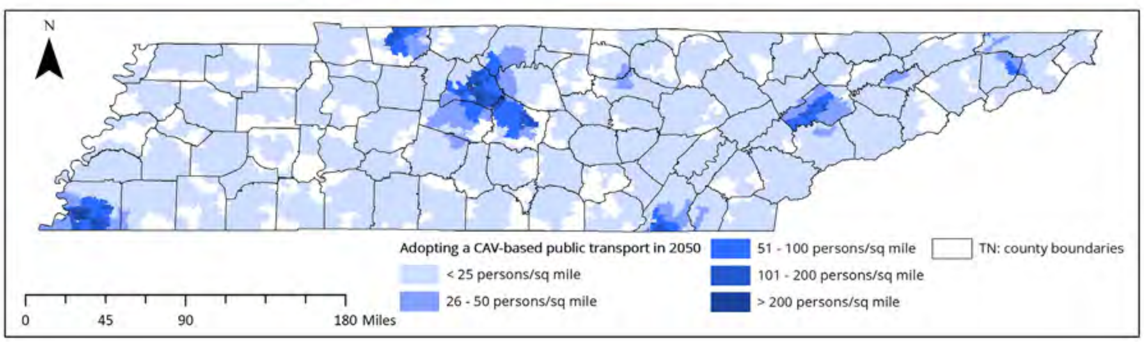
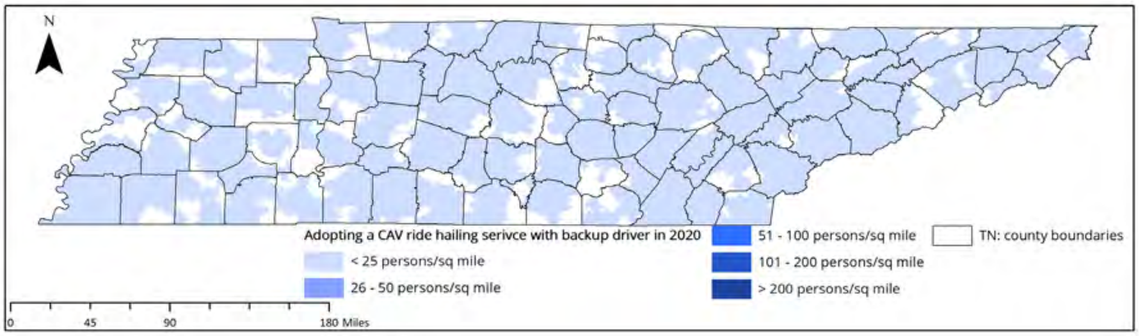


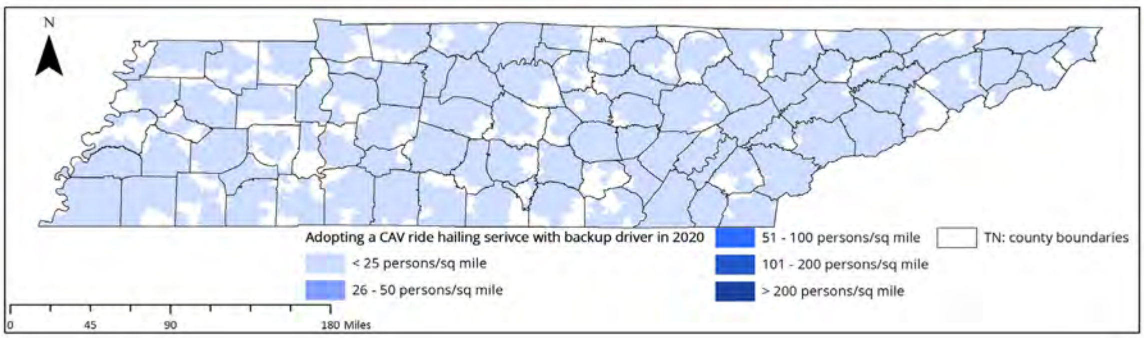
(c)

Figure B.2

Tennessee residents adopting a CAV-based public transport (persons/ sq. mile) (a) 2020 (no price reduction) (b) 2050 (5% price reduction) (c) 2050 (20% price reduction)



(a)



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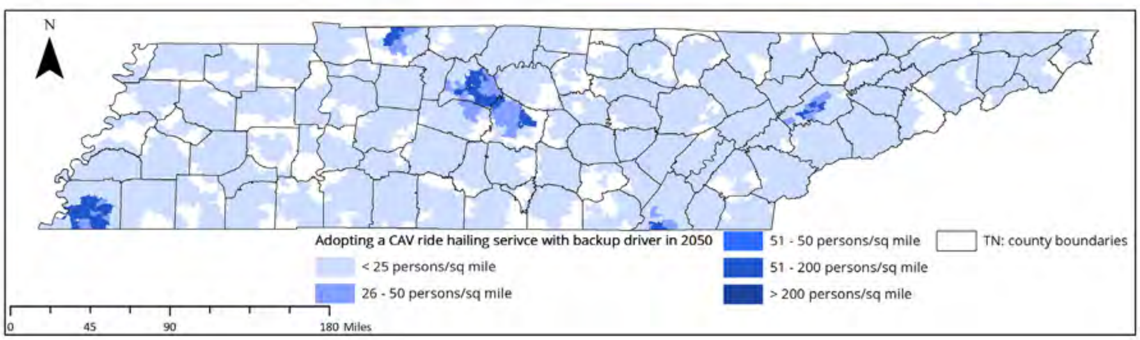
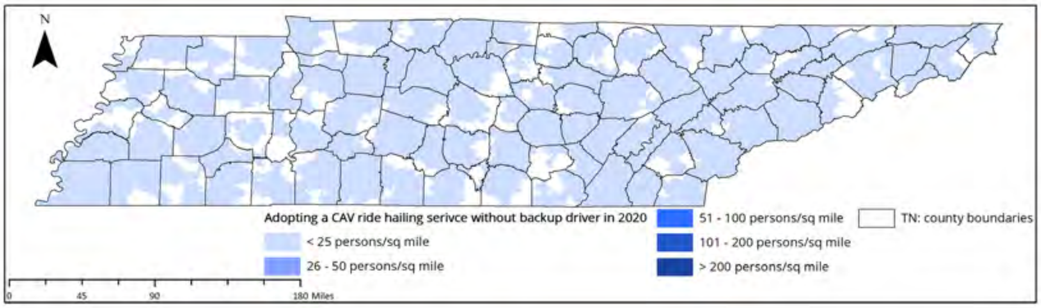


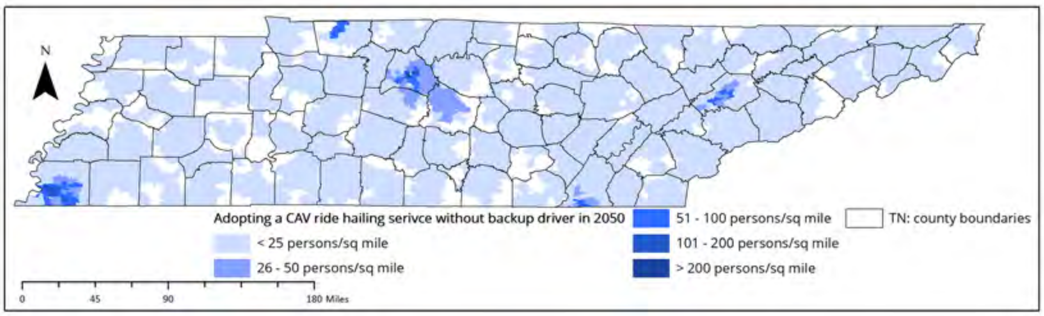
(c)

Figure B.3

Tennessee residents adopting a CAV ride hailing service with backup human driver present (persons/ sq. mile) (a) 2020 (no price reduction) (b) 2050 (5% price reduction) (c) 2050 (20% price reduction)



(a)



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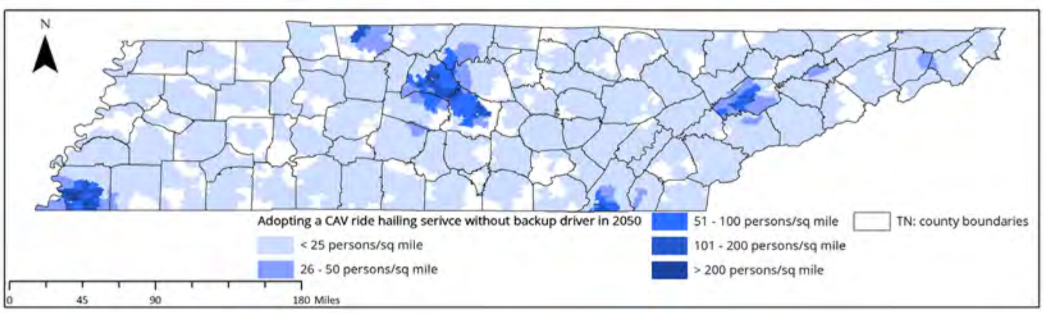
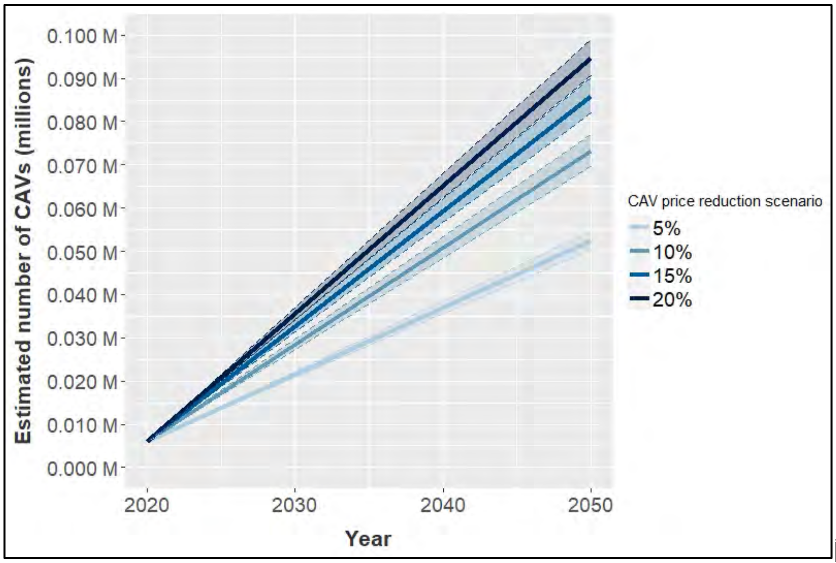


(c)

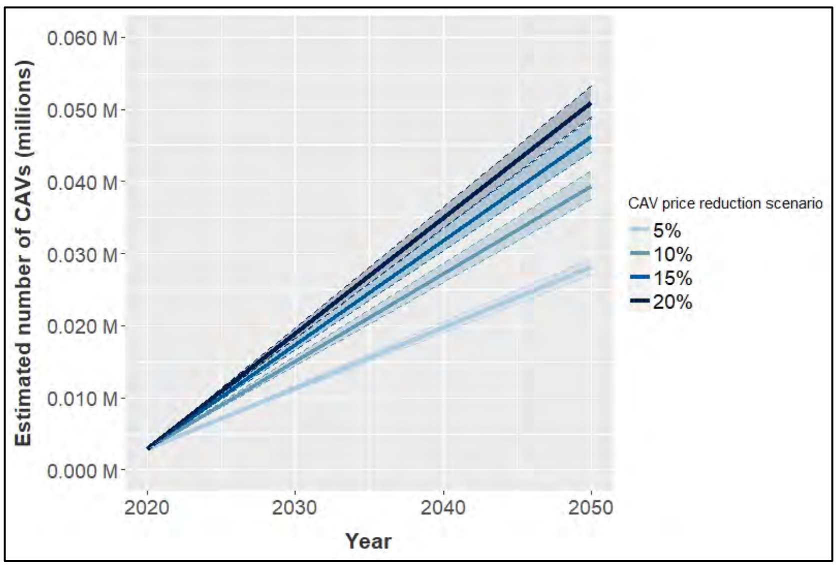
Figure B.4

Tennessee residents adopting a CAV ride hailing service without backup human driver present (persons/ sq. mile) (a) 2020 (no price reduction) (b) 2050 (5% price reduction) (c) 2050 (20% price reduction)



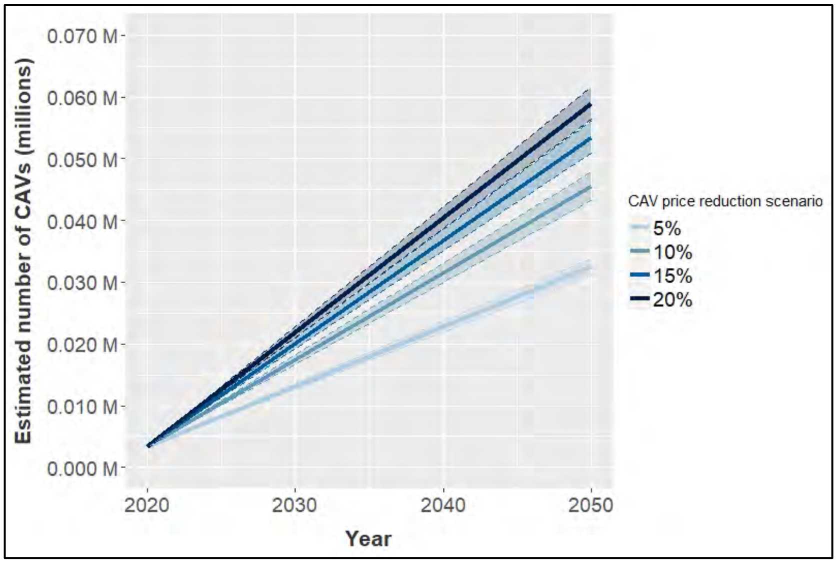
Estimated number of CAVs (millions)
0.100 M
0.090 M
0.080 M
0.070 M
0.060 M
0.050 M
0.040 M
0.030 M
0.020 M
0.010 M
0.000 M
2020
2030
2040
2050
Year
CAV price reduction scenario
5%
10%
15%
20%

(a)

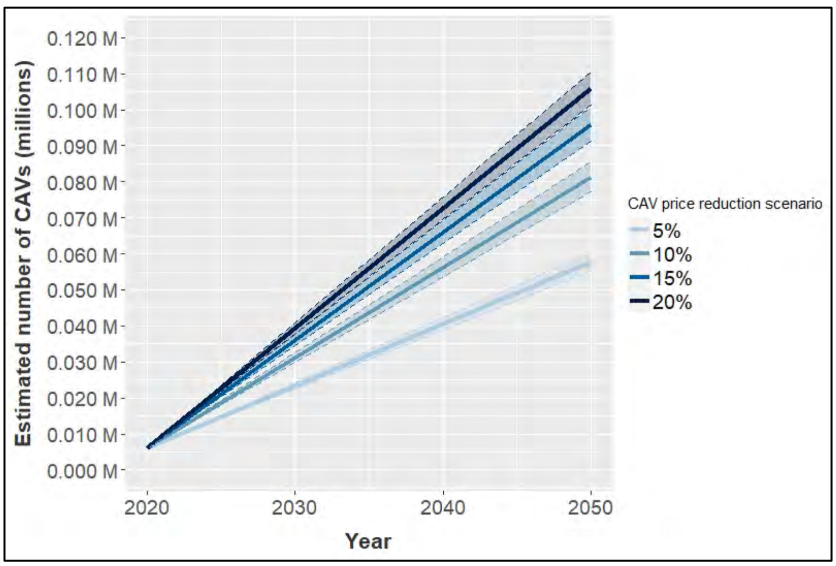


Estimated number of CAVs (millions)
0.060 M
0.050 M
0.040 M
0.030 M
0.020 M
0.010 M
0.000 M
2020
2030
2040
2050
Year
CAV price reduction scenario
5%
10%
15%
20%

(b)



(c)



(d)

Figure B.5

Number of privately owned CAVs in 2020 and four price reduction scenarios in 2050 for the four major counties of Tennessee (a) Davidson (b) Hamilton (c) Knox (d) Shelby

Appendix C. Statewide Survey

Start of Block: Consent and Screening

Autonomous Vehicle Survey

Dear Participant,

Researchers at the Department of Civil Engineering at the University of Memphis, in collaboration with Tennessee Department of Transportation (TDOT), are conducting a research study to understand what individuals with different backgrounds and transportation habits think about Autonomous Vehicles (AV).

You are cordially invited to participate in a survey to help us collect data for this study. We expect the survey will take approximately 15 minutes to complete. Your participation is voluntary, and survey responses will remain COMPLETELY CONFIDENTIAL. Only members of the immediate research team will review the data, and they will review only aggregate-level statistics. Please be aware that if you decide to participate, you may stop participating at any time, and you may decide not to respond to any specific question.

No names or e-mails will be used in any of the analysis or dissemination, and we will not be able to trace any name or e-mail to a specific response. If you choose to complete the survey, you will be given an option to enter a prize drawing by leaving your e-mail at the end of the survey. This e-mail will ONLY be used for the random selection and notification of prize winners. Prize offered for randomly selected survey participants, from 7,000 anticipated participants, is one $10 Amazon gift card with the chance of winning as 1 in 140.

If you have any questions about your rights as a volunteer in this research, contact the Institutional Review Board staff at the University of Memphis at 901-678-2705. Should you have any questions about the survey, please contact Dr. Sabya Mishra (e-mail: smishra3@memphis.edu, phone: 901-678-5043) or Ishant Sharma (e-mail: isharma@memphis.edu, phone: 901-607-7576).

The deadline to complete the survey is at 11:59 PM on XXX, XX XXXX, 2021.

Q2 Do you consent to these terms of participation?

- Yes, proceed (1)
- No, end the survey (2)

Skip To: End of Survey If Do you consent to these terms of participation? != Yes, proceed

Q3 Please indicate your age

- Less than 18 (1)
- 18-24 (2)
- 25-34 (3)
- 35-44 (4)
- 45-54 (5)
- 55-59 (6)
- 60-64 (7)
- 65-74 (8)
- more than 74 (9)
- Prefer not to disclose (10)

Q4 Are you a resident in Tennessee, USA?

- Yes (1)
- No (2)

End of Block: Consent and Screening

Start of Block: Socio-economic Characteristics

Q5 Please indicate your gender.

- Male (1)
- Female (2)
- Prefer not to disclose (3)

Q6 Please indicate your race/ethnicity

- White (1)
- Black or African American (2)
- American Indian or Alaska Native (3)
- Asian (4)
- Native Hawaiian and Other Pacific Islander (5)
- Hispanic or Latino (6)
- Multi-race (7)
- Other (8)
- Prefer not to disclose (9)

Q7 Which of the following best describes your marital status?

- Single (1)
- Married (2)
- Separated (3)
- Widowed (4)
- Living with partner (5)
- Divorced (6)
- Prefer not to disclose (7)

Q8 Which of the following best describes your highest educational attainment?

- Middle school or below (1)
- High School or equivalent (2)
- Some College (3)
- College Graduate (4)
- Master's (MS) or Doctoral Degree (Ph.D.) (5)
- Professional Degree (MD, JD, etc.) (6)
- Other (7)

Q9 What is the approximate amount of your total annual income?

- Less than $10,000 (1)
- $11,000 to $15,000 (2)
- $16,000 to $25,000 (3)
- $26,000 to $35,000 (4)
- $36,000 to $50,000 (5)
- $51,000 to $65,000 (6)
- $66,000 to $75,000 (7)
- $76,000 to $100,000 (8)
- $101,000 to $125,000 (9)
- $126,000 to $140,000 (10)
- $141,000 to $155,000 (11)
- More than $155,000 (12)
- Prefer not to disclose (13)

End of Block: Socio-economic Characteristics

Start of Block: Tech-savvy lifestyle

Q10 How often do you listen to the radio?

- Almost every day (1)
- Once a week or more (2)
- Once a month or more (3)
- A few times a year (4)
- Never (5)

Q11 How often do you watch TV?

- Almost every day (1)
- Once a week or more (2)
- Once a month or more (3)
- A few times a year (4)
- Never (5)

Q12 Do you have a smartphone?

- Yes (1)
- No (2)

Q13 How often do you use your smartphone to control smart home appliances (Google Home, Amazon Alexa)?

- Almost every day (1)
- Once a week or more (2)
- Once a month or more (3)
- A few times a year (4)
- Never (5)

End of Block: Tech-savvy lifestyle

Start of Block: Household and Vehicle Ownership Characteristics

Definition: A household consists of one or more people who live together in the same dwelling and also share meals or living accommodations.

Q15 Which of the following best describes the location of your house?

- Urban setting (1)
- Semi-urban setting (2)
- Rural setting (3)

Q16 Please indicate the number of people living in your household (including yourself).

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 and more (5)
- Prefer to not disclose (6)

Q17 What is the approximate amount of your household's total annual income?

- Less than $10,000 (1)
- $10,000 to $15,000 (2)
- $16,000 to $25,000 (3)
- $26,000 to $35,000 (4)
- $36,000 to $50,000 (5)
- $51,000 to $75,000 (6)
- $76,000 to $100,000 (7)
- $101,000 to $125,000 (8)
- $126,000 to $140,000 (9)
- $141,000 to $150,000 (10)
- $151,000 to $200,000 (11)
- More than $200,000 (12)
- Prefer not to disclose (13)

Q18 How many cars does your household own?

- 0 (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 or more (5)
- Prefer to not disclose (6)

Q19 How many cars has your household purchased over the last 10 years?

- 0 (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 or more (5)
- Prefer to not disclose (6)

Q20 How many USED CARS has your household purchased over the last 10 years?

- 0 (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 or more (5)
- Prefer to not disclose (6)

Q21 Please rate how important each of the following factors are to your car purchasing decisions:

	Very Unimportant (1)	Unimportant (2)	Somewhat Unimportant (3)	Neutral (4)	Somewhat Important (5)	Important (6)	Very Important (7)
Price of the car (1)	•	•	•	•	•	•	•
Quality of the car (2)	•	•	•	•	•	•	•
Environmental impact (3)	•	•	•	•	•	•	•
Personal image (people say WOW) (4)	•	•	•	•	•	•	•
Eliminating multiple unexpected trips to the service station (5)	•	•	•	•	•	•	•

Q22 How frequently does your household purchase a car?

- Once per year (1)
- Once every 2-3 years (2)
- Once every 5 years (3)
- Once every 10 years (4)
- Once every 15 years (5)
- Once every 20 years or more (6)
- Prefer to not disclose (7)

Q23 Does your household plan to buy or sell a car in the next two or three years?

- No (1)
- Yes - buy a new car and keep the current car(s) (if any) (2)
- Yes - buy a new car and sell my current car(s) (3)
- Yes - buy a used car and keep my current car(s) (if any) (4)
- Yes - buy a used car and sell my current car(s) (5)
- Yes - sell the current car(s) and not buy a car (6)

Q24 Assume that your household plans to buy a car in the next two or three years. How much would your household be willing to pay on the car? (Total Purchase Price)

- Less than $5,000 (1)
- $5,100 to $10,000 (2)
- $10,100 to $15,000 (3)
- $15,100 to $20,000 (4)
- $20,100 to $25,000 (5)
- $25,100 to $30,000 (6)
- $30,100 to $35,000 (7)
- $35,100 to $40,000 (8)
- $40,100 to $45,000 (9)
- $45,100 to $50,000 (10)
- $50,100 to $60,000 (11)
- $60,100 to $70,000 (12)
- $70,100 to $80,000 (13)
- $80,100 to $90,000 (14)
- $90,100 to $100,000 (15)
- More than $100,000 (16)

End of Block: Household and Vehicle Ownership Characteristics

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Start of Block: Work and Travel Related Activities

Q25 How often do you work from home?

- Almost every day (1)
- Once a week or more (2)
- Once a month or more (3)
- A few times a year (4)
- Never (5)

Q26 How flexible is your work schedule?

- Flexible: Can start any time (1)
- Somewhat flexible: Can start within a few hours of the scheduled time (2)
- Inflexible: Have to start at a specific scheduled time (3)

Q27 Do you have any of the following conditions that limit your ability to drive yourself? (You may select more than one option)

- No (1)
- Yes, limited mobility (wheelchair, walker, cane) (2)
- Yes, vision impairment (3)
- Yes, hearing impairment (4)
- Yes, mental impairment (5)
- Yes, other conditions (6)
- Prefer not to disclose (7)

Q27 Do you have any of the following conditions that limit your ability to drive yourself? (You may select more than one option)

- No (1)
- Yes, limited mobility (wheelchair, walker, cane) (2)
- Yes, vision impairment (3)
- Yes, hearing impairment (4)
- Yes, mental impairment (5)
- Yes, other conditions (6)
- Prefer not to disclose (7)

Q28 How often do you use your smartphone to complete travel related activities (GPS navigation)?

- Almost every day (1)
- Once a week or more (2)
- Once a month or more (3)
- A few times a year (4)
- Never (5)

Q29 How much is your estimated annual vehicle mileage?

- Less than 1000 miles (1)
- 1000-3000 miles (2)
- 3000-5000 miles (3)
- 5000-10000 miles (4)
- More than 10000 miles (5)

Q30 Do you have any past experiences with vehicle crashes?

- Yes (1)
- No (2)

Q31 How often do you use following travel modes for your daily commute?

	Almost every day (1)	Once a week or more (2)	Once a month or more (3)	A few times a year (4)	Never (5)
Personal vehicle (2)	•	•	•	•	•
Public transport (3)	•	•	•	•	•
Ride-sharing taxi services (UberPool, LyftShare) (4)	•	•	•	•	•
Ride-hailing taxi services (UberX, LYFT) (5)	•	•	•	•	•

End of Block: Work and Travel Related Activities

Start of Block: Autonomous Vehicles

Q32 Have you heard about autonomous cars (Google Waymo, Tesla)?

- Yes (1)
- No (2)

Q33 Assume your household has the option to purchase an autonomous car. How much MORE would you be willing to pay for an autonomous car than you would be willing to pay for a standard car (one you must operate)?

- Less than $2,500 (1)
- $2,600 to $5,000 (2)
- $5,100 to $7,500 (3)
- $7,600 to $10,000 (4)
- $10,100 to $15,000 (5)
- $15,100 to $20,000 (6)
- $20,100 to $25,000 (7)
- $25,100 to $30,000 (8)
- $30,100 to $35,000 (9)
- More than $35,000 (10)

Q34 If autonomous cars could be capable of making trips to service stations on their own, will you be willing to pay more to buy them?

- Yes (1)
- No (2)

Q35 How much MORE in YEARLY maintenance costs would your household be willing to pay for an autonomous car than you would be willing to pay for a standard car (one you must operate)?

- $0 more (1)
- Less than $100 (2)
- $100 to $300 (3)
- $300 to $500 (4)
- $500 to $1,000 (5)
- More than $1,000 (6)

End of Block: Autonomous Vehicles

Start of Block: Social Network

Note: Note that the following questions relate to YOURSELF

Q37 How many "close social ties" have you established at work? (Here, a "close social tie" refers to the relationship between two persons who relatively frequently talk to each other about non work-related matters.)

Q38 At work, how many people in your social network have reliable information about cars?

- No one (1)
- 1 person (2)
- 2 people (3)
- 3 people (4)
- 4 people (5)
- 5+ people (6)
- Do not know (7)

Q39 How frequently do you communicate with the social ties you have developed at work?

- Every day (1)
- 2-3 times per week (2)
- 2-3 times every couple of weeks (3)
- 2-3 times per month (4)
- Once per month (5)
- Once every few months (6)

Q40 When deciding whether or not to purchase an autonomous car, how would you rate the reliability of the following sources of information

	Very Unreliable (1)	Unreliable (2)	Somewhat Unreliable (3)	Neutral (4)	Somewhat Reliable (5)	Reliable (6)	Very Reliable (7)
A friend/co-worker who has already purchased an autonomous car (1)	•	•	•	•	•	•	•
Media Advertisements (Print, Television, Radio, Internet) (2)	•	•	•	•	•	•	•
Car dealer (3)	•	•	•	•	•	•	•
Personal research (YouTube videos and blogs) (4)	•	•	•	•	•	•	•

Q41 When purchasing an autonomous car, how important is input from the following sources:

	Very Unimportant (1)	Unimportant (2)	Somewhat Unimportant (3)	Neutral (4)	Somewhat Important (5)	Important (6)	Very Important (7)
My work social network (1)	•	•	•	•	•	•	•
My non-work social network (3)	•	•	•	•	•	•	•

End of Block: Social Network

Please read this explanation before answering next questions: Autonomous car is a vehicle that is capable of sensing its environment and navigating without human input. No driver attention is required for safety, i.e., the driver may safely go to sleep or leave the driver's seat. Autonomous operation is only supported under certain circumstances and areas. Outside of these areas or circumstances, the car will be able to safely abort the trip, i.e. park the car, if the driver does not retake control.

Q43 How important are the following considerations:

	Very Unimportant (1)	Unimportant (2)	Somewhat Unimportant (3)	Neutral (4)	Somewhat Important (5)	Important (6)	Very Important (7)
The autonomous feature does not work in areas with a poor internet connection (1)	•	•	•	•	•	•	•
An autonomous car may lose internet connection and quit the autonomous mode (in this case, the driver should take control, or the car will park safely) (2)	•	•	•	•	•	•	•
There is a risk that the computer system operating an autonomous car may fail resulting in unexpected operations (3)	•	•	•	•	•	•	•
There is a risk that the computer operating an autonomous car may be attacked by a virus resulting in unexpected operations (4)	•	•	•	•	•	•	•
An autonomous car might not be as agile and maneuverable as regular cars when on auto- driver mode (5)	•	•	•	•	•	•	•
A computer will have full control over my car and daily travel related data. (6)	•	•	•	•	•	•	•
An autonomous car might not be as safe as a standard car	•	•	•	•	•	•	•

(the one you must operate) (7)							
By having an autonomous car, I may lose some friends who are not likely to purchase an autonomous car (8)	•	•	•	•	•	•	•

Q44 How important are the following considerations:

	Very Unimportant (1)	Unimportant (2)	Somewhat Unimportant (3)	Neutral (4)	Somewhat Important (5)	Important (6)	Very Important (7)
An autonomous car can be synced with traffic lights and other vehicles to decrease my travel time (1)	•	•	•	•	•	•	•
An autonomous car may generate less pollution compared to a standard car (the one you must operate) (2)	•	•	•	•	•	•	•
Annual maintenance costs for an autonomous car maybe a few hundred dollars more than for regular cars (3)	•	•	•	•	•	•	•
An autonomous car can provide a greater degree of mobility for someone with a physical, visual, or other forms of impairment (4)	•	•	•	•	•	•	•
An autonomous car can provide an increased level of productivity while traveling (5)	•	•	•	•	•	•	•
Having an autonomous car could improve my status among my peers (6)	•	•	•	•	•	•	•
Having an autonomous car could decrease my	•	•	•	•	•	•	•

car insurance premium (7)							
Having an autonomous car could decrease time spent in parking the vehicle and monthly parking costs (8)	•	•	•	•	•	•	•

End of Block: Autonomous cars: barriers and benefits

Start of Block: Mode choice

Q45 How interested are you to choose the following travel modes for your daily commute?

	Very Uninterested (1)	Uninterested (2)	Somewhat Uninterested (3)	Neutral (4)	Somewhat Interested (5)	Interested (6)	Very Interested (7)
An autonomous taxi with the backup driver present (1)	•	•	•	•	•	•	•
An autonomous taxi with no backup driver present (2)	•	•	•	•	•	•	•
Own an autonomous car (3)	•	•	•	•	•	•	•
Share an autonomous car (carpool) (4)	•	•	•	•	•	•	•
An autonomous bus transit service (public transport) (5)	•	•	•	•	•	•	•

End of Block: Mode choice

Start of Block: Rewards

Q46 Do you want to enter a chance to win a $10 Amazon gift card?

- Yes (1)
- No (2)

End of Block: Rewards

These were all the questions we had for you today. Thank you for taking the time to complete this survey. You may close this window.

We truly value the information you have provided. Your responses will contribute to our analyses of the adoption of Autonomous cars in Tennessee.

Click here to know more about this project: "The Impacts and Adoption of Connected and Autonomous Vehicles in Tennessee".

Click here to know more about the project sponsor "Tennessee Department of Transportation (TDOT)".

Click here to know more about the research and innovation at The University of Memphis.