Modeling Adoption of Technological Innovations and Infrastructure Impacts in a Smart City

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DISCLAIMER

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Executive Summary

Connected Autonomous Vehicles (CAVs) have the potential to revolutionize transportation. Recent technological breakthroughs in CAV technology have led manufacturers to promise a level of automation by 2020. Among some of the expected benefits of CAVs are a reduction in collisions, increased fuel efficiency, and decreased congestion on the roadways. CAVs will also make transportation easier for disabled, elderly, and children who are unable to operate a traditional vehicle on their own. However, before CAVs are ready to integrate into the vehicle fleet, there are a number of important questions which must be answered. Questions about liability, safety, security, legality, registration, and privacy must be addressed before CAV technology can be fully adopted by the public. In order for policymakers to adequately prepare for CAVs, a reasonably accurate estimation of the market penetration rate of CAVs is needed. Predicting the number of CAVs that will need to be accommodated will allow policymakers to develop appropriate legislation.

The objective of this research is to understand, model, and predict CAV market penetration over time. We conducted a survey of University of Memphis employees to understand the perception of users towards CAVs. The model is based on Diffusion of Innovations (DoI) theory, which states that an individual is influenced by both personal desire and social pressures to adopt innovations. A synthetic population and network of unique agents are generated from survey data, and these agents choose to adopt or reject CAVs based on various factors such as personality, socioeconomic status, perceived barriers to adoption, and connections to other adopters.

The report is organized into five sections. Section 1 outlines the introduction and the background of the report. Section 2 contains the literature review related to CAVs, DoI, and ABM. Section 3 details the methodology of the study, and Section 4 contains the survey data and analysis. Section 5 concludes the report.

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1 INTRODUCTION

1.1 Background

Decades ago, self-driving cars were nothing more than a fantasy. However, completely automated vehicles (CAVs) are soon to become a reality, and they are arriving much earlier than many would think. Most commercially available cars today have already achieved a small degree of automation with features such as parking assist, adaptive cruise control, and collision avoidance systems, and Google, Mercades, Tesla, and others have already developed and tested prototypes of the first fully autonomous vehicles. There has been significant research and development on the operational side of making automated vehicles a reality, but the question of demand has received little attention from academia.

The demand for CAVs depends on how quickly the technology is adopted by the consumer. New technology is never universally accepted as soon as it becomes commercially available because it is usually too expensive and inefficient for the average consumer. For example, hybrid vehicles became commercially available in 1997, but even today they only represent a small portion of vehicle sales due to inherent higher costs and usability issues such as insufficient battery life *(1)*. Even when technology becomes affordable, not all consumers will adopt it simultaneously. Smartphones have been available, affordable, and efficient for many years, and yet studies still show that there is a significant number of American adults who do not own a smartphone, or even a cell phone at all *(2)*.

There has been a great deal of research done to try to understand why some people readily adopt new technologies and innovations, while others tend to resist change. No unified model exists that accurately describes the process of an individual adopting an innovation *(3)*. However, empirical studies have been conducted in multiple fields to examine how readily people accept new technologies. Papers have been published investigating adoption of cell phones *(4)*, the internet *(5)*, and hybrid cars *(6)*. But there have been very few studies on the future adoption of CAVs.

1.2 Problem Statement

While manufacturers are certain that CAVs will soon be ready for consumers, a number of concerns remain regarding the new technology. Before CAV technology can be adopted, policymakers must address concerns over liability, legality, registration, safety, security, and privacy. Among other information, policymakers require an estimate of how quickly CAVs will be adopted by the public. One method of predicting the adoption of CAVs which has not been fully explored is the diffusion of innovations theory. Diffusion of innovations theory has been successfully used in many fields to investigate the way innovations have been assimilated into that field, and it can be used for CAV technology, as well.

1.3 Section Summary

The findings of this study are expected to aid policymakers as they prepare the transportation infrastructure for autonomous vehicles. The information will also be valuable for vehicle manufacturers and for potential consumers of CAVs.

The report is organized into five sections. Section 1 outlines the introduction and the background of the report. Section 2 contains the literature review related to CAVs, DoI, and ABM. Section 3 details the methodology of the study, and Section 4 contains the survey data and analysis. Section 5 concludes the report.

2 LITERATURE REVIEW

2.1 Connected Autonomous Vehicles

The existing studies on adoption of CAVs can be grouped into two categories: those which focus on investigating the general perception of CAVs by the general public, and those which use a variety of predictive models to attempt to forecast the future demand for CAVs and SAVs (Shared Automated Vehicles).

The studies that concern themselves with the overall opinion of consumers are able to draw a number of conclusions, most of them vague and inconclusive. Schoettle and Sivak (2014) conduct a survey across the U.S., U.K., and Australia, and find that there is very little difference in perception of CAVs across country lines. People generally feel optimistic about the potential of CAVs, but are concerned about the safety and reliability of the automation systems. U.S. respondents are more concerned with potential legal and safety issues than their U.K. and Australian counterparts, and respondents from all three countries are generally worried about riding in a CAV with no driver controls whatsoever *(7)*. Kyriakidis et al. (2015) gathers data from non-Western countries as well as more commonly surveyed countries such as the U.S. and U.K. They find that there is a wide spread of Willingness to Pay, or WTP and opinion of CAVs across country lines, age, and income levels. They report that a large portion of the population have fully embraced the concept of automated driving, while another portion are reluctant and skeptical of the notion of CAVs *(8)*. Zmud et al. (2016) use online surveys and face-to-face interviews, and conclude that half of the population has a favorable outlook on the future use of CAVs. However, they note that people generally have a low WTP, meaning that most people are not willing to pay very much to acquire automation. The majority of respondents prefer the thought of owning their own self-driving car rather than utilizing a ride-sharing system such as Uber, citing the convenience of owning a car as the primary reason *(9)*. Daziano et al. (2016) analyzes WTP for the different levels of automation in vehicles using discrete choice experiments with "realistic choice settings," where they offer various levels of automation at randomly generated prices. They find such a wide range of responses that they are unable to conclude with certainty how consumers feel about CAVs. Some portion of the population seem open to paying upwards of $10,000 extra for full automation, but Daziano warns that there is too much variance in the responses to draw any significant conclusion *(10)*.

Those that attempt to predict the future demand of CAVs used a wide variety of predictive models and methods. Zmud et al. (2016) states that the research in this area covers a variety of different methodologies, sources of data, and variables, resulting in inconsistent results and difficulty in comparing the findings of these studies. Despite this, it is still useful to identify what methods are being attempted and what conclusions are being drawn from them *(9)*.

Bansal and Kockelman (2016) use Monte Carlo simulations and multi-nominal logit models to predict how likely a household is to buy, sell, or upgrade a vehicle in any given year. They run eight different scenarios where the variables considered are (i) an increase in annual WTP levels, (ii) an annual reduction in technology costs, and (iii) government regulations requiring automation in vehicles. From these 8 scenarios, they conclude that fully automated vehicles will likely be adopted by 24.8 - 87.2% of the vehicle fleet by the year 2045 – an estimation that is too broad to be considered conclusive *(11)*. Krueger et al. (2016) uses a stated choice survey analyzed using a mixed logit model in an attempt to determine the characteristics of individuals who are most likely to adopt shared automated vehicles (SAVs). They conclude that those who currently use ride-sharing systems (Uber and Lyft, for example) are much more likely to readily adopt SAVs than those who exclusively drive themselves. They also note that the purpose of the hypothetical trip has a significant effect on the decision to use personal transport or SAVs. For example, individuals are less likely to utilize SAV services for doctor appointments than for routine transit to their workplace *(12)*. Bansal et al. (2016) uses bivariate ordered probit models to estimate how attractive the idea of CAVs and SAVs will be to consumers at various prices, focusing less on the consumer's qualities and more on the perceived economic benefits of the system. They conclude that the average WTP for fully automated vehicles is over $7000, and over 80% of their respondents showed an interest in owning a CAV *(13)*. Lavasani et al. (2016) uses a generalized Bass diffusion model to predict how CAVs are likely to be adopted into the general marketplace. Because CAVs have not actually been introduced to consumers, they are forced to use data from the adoption of previous technological innovations such as hybrid cars, cell phones, and the internet *(14)*.

2.2 Diffusion of Innovations Theory

A method of predicting CAV market penetration which the literature has not explored is diffusion of innovations. Popularized by Everett Rogers, this theory attempts to explain how, why, and how quickly an innovation or technological advancement spreads through a social system. The theory differs from previously used methodologies because it contains a significant behavioral component that other methods lack. The theory considers how one adopter may influence others to adopt or reject an innovation. It also investigates the communication channels that provide a potential adopter with information.

Rogers (2010) lists the five major characteristics of an innovation that affect its adoption rate: relative advantage, compatibility, complexity, trialability, and observability. Relative advantage is the benefit of adopting an innovation compared to rejecting it. This characteristic can be measured in economic terms if an innovation can save time or money, or in social terms if adopting an innovation is considered desirable or prestigious. For example, CAVs will allow their drivers to read, write, and perform other activities while commuting that they cannot with a standard vehicle. Decreased crash rates, better fuel economy, and ease of use are all examples of the relative advantage that CAVs may offer consumers. Compatibility with the needs or desires of the adopter is highly based on the perception of the individual. Complexity has an inverse relationship with adoption rate; the more complex an innovation is, the slower it is likely to be accepted. This may prove to be a barrier to CAV adoption, because potential adopters will not fully understand how the system works, and they may not trust the system as a result. Trialability is an important quality to consider when examining the adoption process, as most individuals prefer to test an innovation before committing. Car rentals and test drives are an easy way for potential adopters to test CAVs before adopting. Observability is also an important characteristic because an innovation that potential adopters can actively observe will be noticed and accepted much easier than an innovation which is not immediately apparent to adopters. Most of the variance in the adoption rate of an innovation can be explained by these five characteristics *(15)*.

Mahler and Rogers (1999) use diffusion of innovations theory to examine how twelve different communication innovations diffused over banks in Germany. They categorize non-diffusing innovations into three groups: bad service from the provider or the innovation itself, socio-technical reasons such as a lack of appropriate standards, organizational issues, or a lack of security, and general low diffusion of the innovation across other banks, which reduced the usefulness of the innovation to the respondent. They also group the banks by their relative innovativeness to better understand the rate at which the new communication innovations were spreading to reluctant adopters *(16)*. Greenhalgh et al. (2004) uses diffusion of innovations theory to investigate the spread of various innovations within the United Kingdom Health Service organizations. They differentiate between "diffusion" and "dissemination," stating that diffusion is the passive spread of an invention, and dissemination is an active attempt to persuade organizations to adopt the innovation. They also identify additional innovation characteristics which are relevant to the adoption of their investigated innovations: level of risk to the organization, relevance to the problem that the innovation is intended to solve, the level of training or knowledge required to adequately use the innovation, and the ease of accessing the needed training or knowledge *(17)*.

2.3 Agent-Based Modeling

Discrete choice modeling has been the prevailing method for forecasting the demand for autonomous cars *(18-21)*. Choice models try to capture decision markers' preferences amongst the set of available alternatives. Choice modeling studies suggest that the light-duty vehicle fleet in the US is not likely to be near homogeneous by 2045. While choice models are helpful tools in estimating adoption trends and understanding the relative importance of factors impacting adoption of CAVs, they fail to capture the effects that adoption of an individual may have on other individuals within his/her network. Discrete choice models forecast the market penetration of CAVs based on the notion of stated preference meaning that they mostly assume that the agents' expectation are the same as market outcome. This assumption, known as rational expectations, is not valid when a radical innovation is introduced as consumers have no previous experience on which they can base expectations *(22)*. In such cases, individuals heavily rely on the information they receive from their peers *(23, 24)*. This diffusion of information becomes more interesting and hard to neglect when virtual social networks and various levels of information transfer among individuals are considered in modeling the adoption process. Figure 2 illustrates the importance of incorporating diffusion of information into the forecasting process. Panel (a) shows adoption when only economic viability of the innovation is considered. Similar curves are widely seen in forecasting market penetration of various products using discrete choice modeling. Adoption curve is observed to be a S-curve when only information exchange with peers is considered (Panel (b)). In the latter case, one can imagine that an individual will purchase a product when s/he observes that a large number of his/her connection have adopted the innovation *(25)*. In real world, both factors, i.e., economic viability and network pressure, affect an individual's decision regarding when to adopt. As a result, *actual* adoption trend will be a mix of the two drivers as is illustrated in Panel (c) in Figure 2. In the latter figure, Alpha denotes the relative importance of social pressure against economic viability.

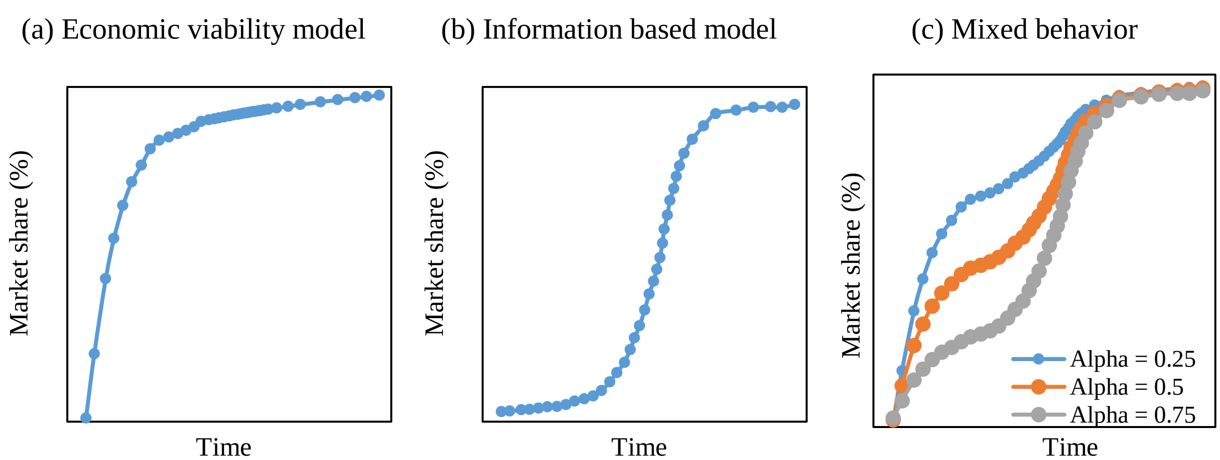

Figure 1 Comparison of drivers of adoption behavior

One promising avenue for forecasting the demand for CAVs is employing the theory of **DOI**. Unlike traditional choice modeling, one important aspect of the DOI theory is understanding the spread of innovations by modeling the perspective of communications and consumer interactions in a network. Diffusion theory accommodates behavior of mixed categories of adopters of innovations. In a smart city environment, different stakeholders have different rates and behaviors of adoption of innovations, and thus the theory of DOI can effectively help explain the overall transition to a smart transportation system. While DOI theory has been used to forecast adoption of electric vehicles *(26-30)*, its application to smart transportation systems is limited. To our best knowledge, application of DOI theory is limited to aggregate-level modeling of adoption of autonomous cars *(31)*. DOI literature fails to explain how trucking and freight agencies adopt autonomous vehicles. The process of adoption of smart infrastructure systems by governmental agencies is also neglected by researchers. Moreover, modeling interdependencies among different stakeholders is absent from the literature.

Here we propose a behavioral adoption approach to model how market penetration of autonomous cars will evolve over time. Automobile manufacturers certainly realize the benefits of autonomous vehicles but this is not the case for typical consumers who are resistant to innovations, especially revolutionary ones, as they change their established routines and day-to-day existence. Three characteristics of resistance are worth to mention. First, each of the previously mentioned seven groups has a certain level of resistance and that level changes the adoption time. Second, there exists a continuum of resistance: from passive resistance (inertia) to active resistance. Third, various classes of products have different resistance as the conflict with the consumers' routines differently (compare evolutionary against revolutionary innovations). These behavioral resistances (barriers) are categorized into two groups *(32, 33)*:

- Functional barriers (arise when there are conflicts with the consumers' prior beliefs)
    - Product usage patterns: this barrier, which is the most common barrier, is realized when the innovation is incompatible with the existing practices, habits, and workflows. Inability to use autonomous feature in areas with low internet coverage is one example of usage barrier.
    - Product value: the value of an innovation can also be a barrier. Some consumers will adopt only if the ratio of performance over value for CAVs is greater than that for tradition cars. Product value, however, could be a less stringent constraint for snob buyers or environmentally conscious users.
    - Risks: the risk barrier induced when the users have uncertainty about the *actual* consequences of adoption. Risks could be functional (usage and economic) or psychological. The risk of malfunctioning due to operating system crash, virus infiltration, and disconnection from internet is an example of functional risk (usage risk) barrier for

CAVs. Another functional risk (economic risk) relates to the fear of higher than expected maintenance costs for CAVs. Loosing or having less relationship with friends with traditional cars can be an example of psychological risk. The latter example specifically pertains to social circles with aggressive driving behavior.

- Psychological barriers (arise when there are conflicts with the consumers' prior beliefs)
  - Traditions and norms: tradition barrier appears when consumers are not willing to adopt because CAVs will change their habits and routines and thus ultimately result in discomfort. For example, users of traditional cars change their lane, path, and speed at any time; thus, the notion that a computer system will have the full power of the automobile can hinder them from adoption.
  - Perceived product image (image barrier): the difference between the product's image and the consumer's perception leads to a barrier obstructing adoption. For instance, those consumers preferring agile, highly maneuverable automobiles, the CAVs' image will be a barrier to adoption.

As the number and intensity of resistances realized by an individual increase, s/he starts to defer adoption of CAVs. Three factors can impact the above factors and facilitate the adoption process *(32, 34, 35)*:

- Mass communication (marketing): media can target a broad spectrum of consumers to reduce both functional and psychological barriers. Marketing, for example, can convince consumers that CAVs will not have substantially higher maintenance cost (functional risk barrier) or they can take the full power of their vehicles at any time (tradition barrier). Note that marketing reduces resistance to a limited extent as consumers mostly do not rely on the information received from media to adopt a radical innovation. Furthermore, it is mostly effective at the early stages of adoption decision making.
- First-hand trial: First-hand trial impact individuals at the final stages of making the decision to adopt. First-hand experience can be influential only on functional barriers, and more specifically on usage barriers.
- Communication (word-of-mouth): once individuals received initial information through mass communication, information received from their peers will be the main propeller of innovation diffusion. Communication is considered within a social network in which nodes represent individuals and communication channels are shown using undirected arcs. The impact of word-of-mouth is a function of the quality of communication between each pair of linked agents as well as network topology. The frequency, intensity, and reliability of communication determine the quality of a communication channels. For example, some individuals talk to each other more frequently and some are more communicative; thus there will be a greater influence on the potential adopters

from the adopted agent. Similarly, individuals typically consider a greater weight for the information they receive from an automobile expert within their network *(36)*. The pattern of information diffusion largely hinges upon how the network is structured. More specifically, position of a specific individual in the network can be such that the level of uncertainty toward adoption decreases faster than other individuals *(37)*. Figure 3 illustrates how the structure of network can impact the adoption process. The upper panel of this figure shows a small-world network. We chose a small-world network as such networks are shown to be well representations of many real social networks *(38, 39)*. This network is composed of two subnetworks which were connected through rewiring. There exists a densely interlinked core stratum in the right-hand-side of the subnetwork in which information from the adopted agent C will be quickly transferred to the other five nodes within the core stratum, and then to the agents within peripheral stratum; thus, information is received through at most two steps. In the left-hand-side subnetwork, which is a sparse network, it can take up to four steps that a potential adopter (agent A) receives information from adopted an adopted agent. So, the information flows faster and more conveniently in the right-hand-side subnetwork, and of course, there exists information flow between the two subnetworks. The lower panel of Figure 3 shows the network after an additional round of rewiring. After rewiring, agent A receives the information directly from an adopted agent and agent B will be the most susceptible agent to adoption as it is linked with two adopted consumers.

3 METHODOLOGY

3.1 Population Synthesis

A primary input for any agent-based model is a set of individuals. It is very expensive – and in many cases impossible – to collect a fully disaggregate data for all agents of interest through surveys. Moreover, using such dataset – if can be collected – can be problematic in many countries due to strict privacy laws. An alternative is to combine microdata samples with aggregate data about the true population to generate an artificial population of agents.

Assume that the sample data provides the distributions of a set of attributes for agents referred to as marginal distributions. The objective of population synthesis is to generate a joint distribution from marginal distributions and then sample from it. One way to do so is to multiply the marginal distribution which will be unbiased only if there is no correlation among various socioeconomic variables. In the real world, however, there are strong relationship among socioeconomic variables (for example, age and income are highly correlated). The well-known Iterative Proportional Fitting (IPF) method *(40)* was developed in 1940 to capture the correlations. Since then, various studies attempted to address issues affecting the quality of population synthesis such as simultaneous control of the individual and household variable *(41-43)* and data limitations *(44-46)*. In this study, we use the Iterative Proportional Updating (IPU) algorithm (47) to generate synthetic population matching the marginal distributions of the true population. IPU is particularly designed to generate a synthetic population such that both household- and personal-level attributes of interest are matched with those of true population. The primary sample data collected only involves employees of the University of Memphis, and the analysis will certainly be biased if such sample is inflated to the larger geographical area (e.g., City of Memphis). Therefore, only personal-level attributes of individual are considered which means that some interesting features of IPU algorithm will not be used. In future a richer dataset containing both personal and household information of Memphis citizens can be collected and all strong features of IPU algorithm can be leveraged.

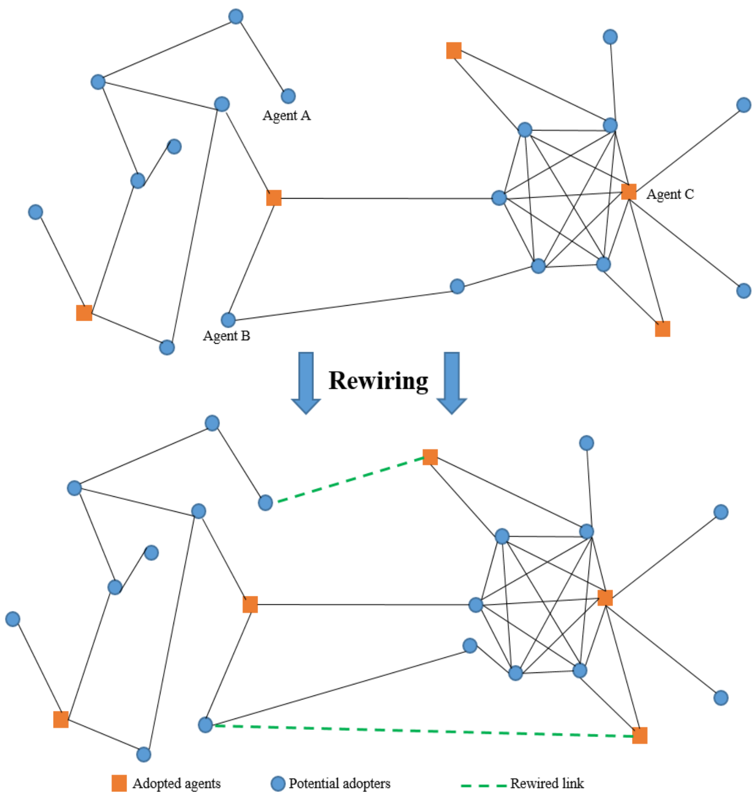

Figure 2 Effect of network topology on adoption

The synthetic population procedure assigns the following attributes to each agent:

1. **Socioeconomic attributes:** gender, marital status, age, income, race, education level, disability, employment status, household size;
2. **Home information:** approximate location of home, dwelling type, factors influenced choosing the current home location;
3. **Vehicle ownership information:** possession of a driving license, length of having a driving license, number of vehicle transactions the household had in the last 10 years, size of the most recent vehicle, fuel type of the most recent vehicle, frequency of car purchasing in the household;
4. **Travel behavior:** mode of commute, flexibility of work schedule, miles driven annually, frequency of teleworking;

5. **Purchasing autonomous vehicles:** willingness to pay, reliability of various sources of information in lowering uncertainty about purchasing an autonomous car;
6. **Social behavior:** number of social ties at workplace (connectivity degree), frequency of communication;
7. **Agent personality:** personality of an agent is a combination of four types: price sensitive, performance seeking, environmentally conscious, snob buyer;
8. **Perceived barriers:** barriers and dis-barriers (incentives) realized by each agent are categorized into four groups:
    a. **Performance (dis-)barriers:**
        i. Autonomous features may not be used in areas with poor internet connection
        ii. An autonomous car may lose internet connection
        iii. An autonomous car can be synced with traffic lights and decrease my travel time
        iv. Considering my disability, an autonomous car can provide a greater degree of mobility to me
        v. There is a risk of virus infiltration into the operating system of autonomous cars
        vi. There is a risk of crashing the operating system of autonomous cars
        vii. I do not like that a computer might have full control over my automobile
        viii. Autonomous cars might not be as agile and maneuverable as regular cars when they are on auto-driver mode
        ix. Autonomous cars are as safe as regular cars
    b. **Environmental dis-barrier:**
        i. An autonomous car can be about less environmentally pollutant
    c. **Value barriers:**
        i. Annual maintenance cost for autonomous vehicles could be about a few hundred dollars greater than that for conventional vehicles
    d. **Image barriers**
        i. Having an autonomous car can bold my status among my peers
        ii. By having autonomous car, I may lose some friends who are not likely to purchase any autonomous car

Each sub-barrier takes a value between 1 and 5. The value of each category is a weighted sum of associated sub-barriers. A weighted some of the four categories will then be calculated using the weights obtained from analyzing personality type of the agent.

3.2 Synthetic Network

Let $G = (V, E)$ be a finite undirected graph representing the ties among individuals, where $V = \{1,2, \dots, i, \dots, N\}$ is the set of vertices (agents) and E, which includes (i, j) pairs, is the set of relationships among vertices V. To develop G using a survey requires a very extensive survey of all individuals in V which is impossible for a real-world problem size. We therefore resorted to establishing a synthetic social network using socio-psychological attributes of agents. The central concept in generating this synthetic social network is the *homophily* principle *(48)* which indicates that the possibility that a pair of agents establish a connection is a function of geographical proximity and socio-demographic similarity. Considering the current data limitations, geographical proximity is defined as being in the same college or division at workplace. Then a 8-dimentional coordinate system is defined by age, gender, race, employment type (faculty, academic staff, non-academic staff), income level, disability status, telework habit, and college/division. Each agent is placed in the 8-dimentional space and the distance between each two agents *i* and *j* are calculated as $D_{ij} = \sqrt{\sum_{m \in S} \omega_m \left(\frac{A_{m_i} - A_{m_j}}{\max d_m}\right)^2}$ where D_{ij} is the distance between agents *i* and *j*, *S* the set of eight attributes of interest, A_{m_k} the value of the m^{th} ($\forall m \in S$) attribute of interest for agent *k*, σ_m the weight for dimension $m \in S$, and d_m maximum value along the m^{th} ($\forall m \in S$) attribute of interest. The impact of the social tie between agent a given *i* and each other agent *j* is defined as $w_{ij} = \frac{D_{ij} - \min_j D_{ij}}{\max_j D_{ij} - \min_j D_{ij}}$. The latter expression gives the weight of the closest agent to the given agent *i* as 1 and farthest as 0. A two-step selection algorithm is developed to choose agents connected to each agent *i*. In real world, individuals typically have up to 25 peers *(50);* thus, the number of social ties is capped at 25 connections.

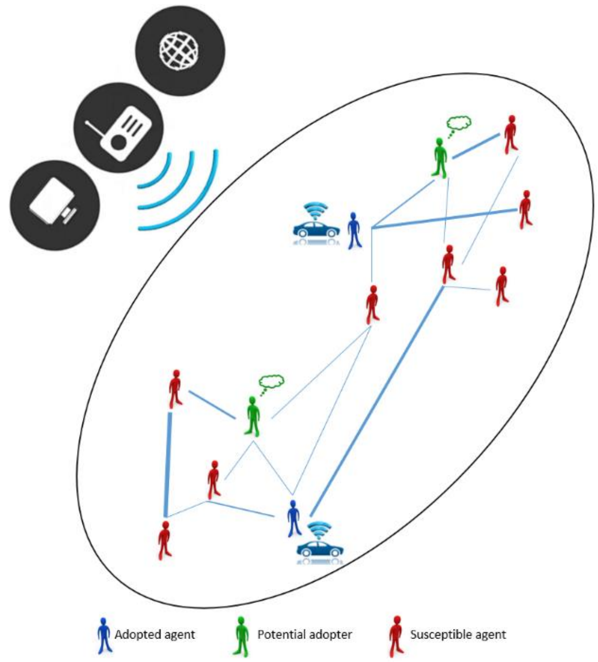

Figure 3 Visualization of framework for modeling personal car adoption

3.3 Perception Dynamics and Agent-Based Simulation

An individual's decision to whether or not purchase any product largely hinges upon how he/she perceives the product's various aspects. An individual's perceptions are dynamic and may change over time as the individuals communicates with his/her peers and is exposed to advertisement. To model this phenomenon, we developed a model of perception dynamics based on the models established in *(49-51)*. Recall from population synthesis that each agent is assigned with a frequency of communication. At each time *t*, each agent *i* may communicate with some agents within its social network. Frequency of communication for any edge is set equal to the minimum of communication frequencies pf the corresponding agents. Given the communication frequency, the next step is to determine how communication and advertisement adjust an individual's opinion. At each time period, the element l of agent i's perception for vehicle type *y* (CAV to conventional) is dynamic and changes according to $X_{i,l,y}^{t+1} = \theta_i X_{i,l,y}^{t} \pm \gamma_i C_{i,l,y}^{t+1,t} + \varepsilon_i M_{i,l,y}^{t+1,t}$, where $C_{i,l,y}^{t+1,t}$ is the effect of communication on agent *i* in time interval [*t*,*t*+1), $M_{i,l,y}^{t+1,t}$ effect of media advertisement on agent *i* in time interval [*t*,*t*+1), θ_i the weight that agent *i* considers for its own opinion, and γ_i and ε_i the weight representing the agent i's trust on communication with its peers and media advertisement, respectively. It is assume that $\gamma_i + \varepsilon_i + \theta_i = 1, \forall i \in V$. The literature suggests that the information received from peers is two to seven times more effective than that from advertisement in newspaper, radio, or magazines (52). Thus one should reasonably expect a higher value for γ_i than ε_i. The social impact on agent i's perception is given by $C_{i,l,y}^{t+1,t} = \sum_{j \in E_i} \frac{w_{ij}\beta_{ij}}{(1+\alpha)^{t+1-t_j'}} X_{i,l,y}^{t}$, where E_i is the agent i's set of peers, β_{ij} effect of word-of-mouth from agent *j* on agent *i*, t_j' the time at which agent j adopted a CAV, and α the dissipation rate of word-of-mouth. The impact of media advertisement is obtained by $M_{i,l,y}^{t+1,t} = \frac{X_{i,l,y}^{t}\tau_i}{(1+\rho)^{t+1}}$, where τ_i is the effect of media advertisement on agent i, and ρ dissipation rate of media advertisement. This function indicates that agents have memory and the effects of media and communication are accumulated over time. At the same time, such effects dissipate at time goes by.

This research assumes that two types of messages are transmitted through communication among agents: positive and negative word-of-mouth (WOM). Some adopted agents may not be satisfied with performance and features of CAVs, and thus start to propagate negative WOM. Behavioral research shows that a dissatisfied consumers talk to more individuals compared to satisfied consumer *(53, 54)*. Moreover, the power of negative WOM is known to be two times greater than that for positive WOM *(56)*. The literature frequently assumes that a fixed portion of consumers (e.g., 5% *(50, 55)*) are dissatisfied with adoption. To account for stochasticity, we assumed that an agent which is about to adopt will be dissatisfied adopter if its random seed is less than 0.05. A dissatisfied agent will never adopt a CAV again but continues to spread negative WOM. It is further assumed that at any time point, a satisfied adopter may become a dissatisfied agent if its random seed in the corresponding time point is less that 0.01.

Having the perception dynamics in place, the next step is to develop the agent-based simulation model to forecast diffusion of CAVs. The simulation process starts with an initiation stage in which each agent's lifetime of vehicle (LF_i) is drawn from a normal distribution. Each vehicle is also assigned with an age at the base year (Age_i^0) drawn from a uniform distribution within the interval $[0, LF_i]$. Based on the age of the existing vehicle and its car purchase behavior, each agent *i* make a decision on whether or not it needs to purchase a car at time *t*. An individual seeking to purchase a car is termed "potential adopter". Individual *I* also updates its perceptions according to the perception dynamics model. It then calculates its total perception index for vehicle type *y* ($I_{i,y}^t$) which is equal to a weighted sum of barriers and incentives for purchasing vehicle type *y*. If agent *i* is a potential adopter, it compares total perception indexes for CAVs and conventional cars and decides which car type it will purchase. This simulation algorithm is illustrated in Figure 4.

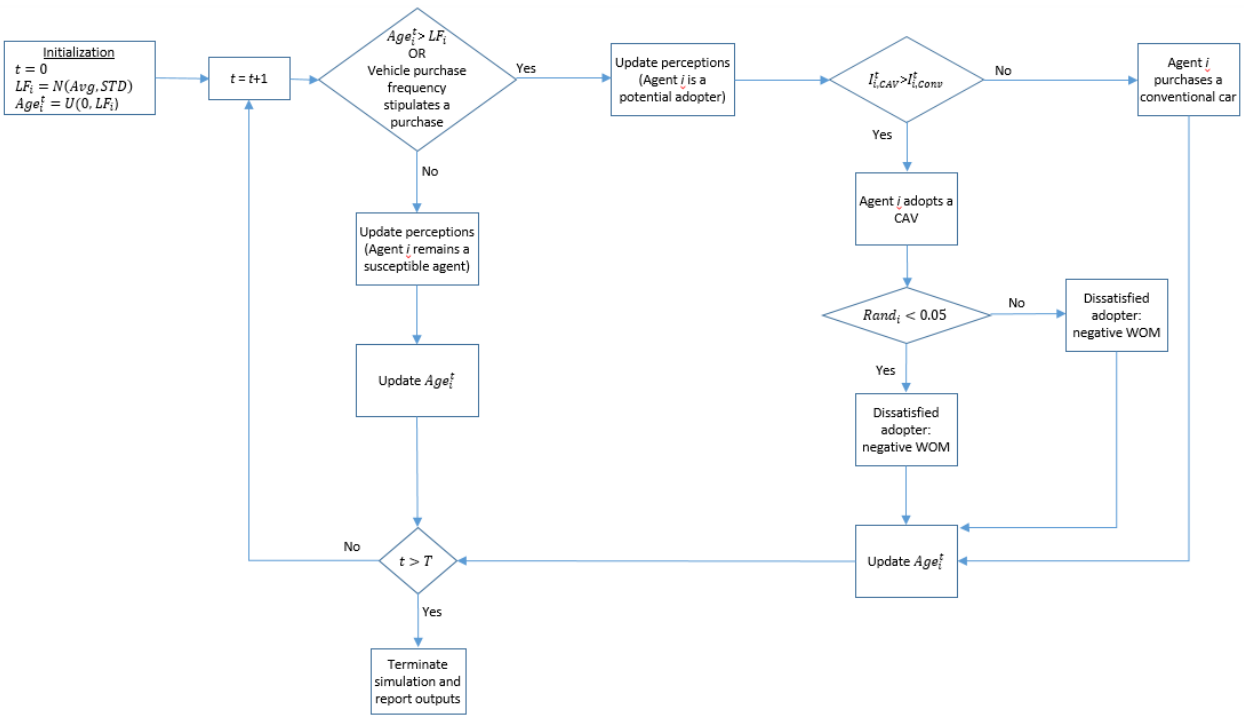

Figure 4 Agent-based simulation algorithm

SURVEY DATA AND RESULTS

4.1 Data Collection

In order to model adoption of CAVs among the university employees, we collected two sets of data: seed and marginal datasets. We conducted a survey to (i) understand how individuals rely on their social network when purchasing a CAV, (ii) how influential the work social ties are, compared to non-work social tis, and (iii) establish a seed for the population synthesis model. The survey comprised of four sections. The first and second sections pertain to personal- and household-level socioeconomic questions. The third section tries to understand various aspects of social network at work, and how individuals rely on their work social ties when purchasing CAVs. The fourth section intended to quantify perceptions toward adopting CAVs. The starting page of the survey on a cellphone device is illustrated in Figure 5, and the survey is attached.

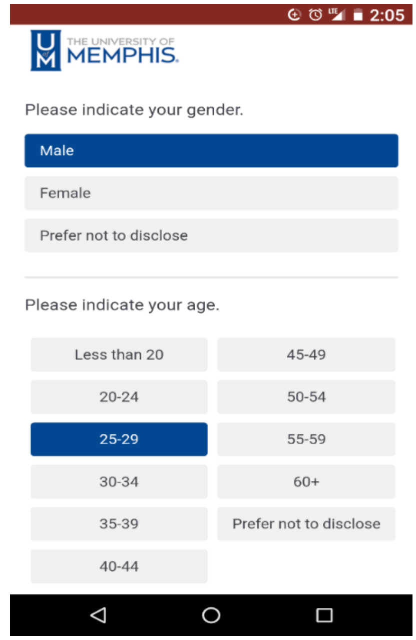

Figure 5: Starting page of the survey on a cellphone

Among 4,504 employees of the University of Memphis, 2,465 employees were contacted through email and asked to complete the survey. We received 334 complete responses (13.5%) in seven days which is a promising rate of response in the field of transportation. The majority of respondents were female (63.6%). The data suggest that individuals consider relatively equal weights for the information they receive from their work and non-work social networks. On a seven-point scale (1 = *very unreliable* to 7 = *very reliable*), individuals consider an average reliability score of 5.58 ($\sigma = 1.08$) for the information they receive from their peers while the reliability scores for media and car dealer were 3.79 ($\sigma = 1.36$) and 3.63 ($\sigma = 1.44$), respectively. This validates the argument that people heavily rely on their peers when adopting a radical innovation. The data is displayed in Figure 6 below.

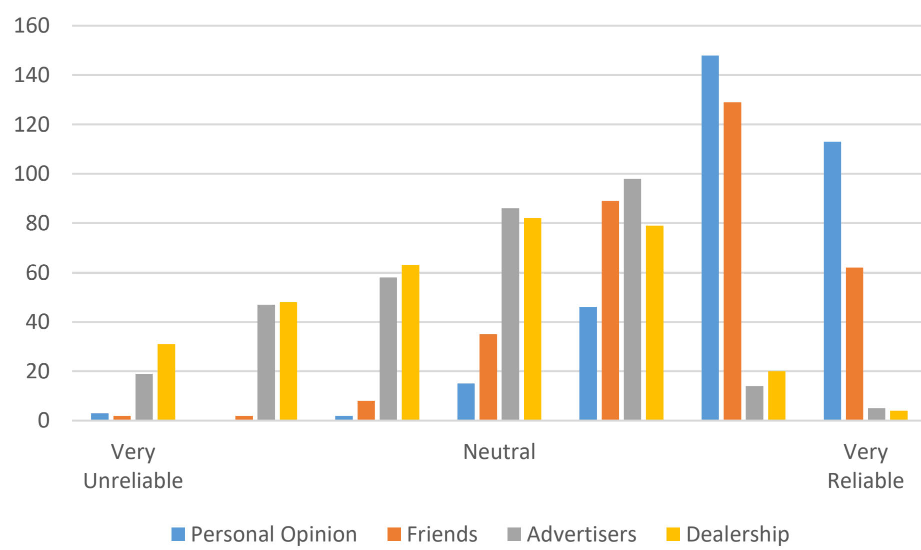

Figure 6 Perceived reliability of influencing factors

Respondents were also asked to consider the importance of various characteristics of CAVs, detailed in Figures 7-9 below. The potential social effects of adopting a CAV seem to be judged as unimportant, whereas safety issues such as the possibility of contracting a virus, losing connections, and OS crashes are very important. Economic and environmental effects of CAVs are also seen as important.

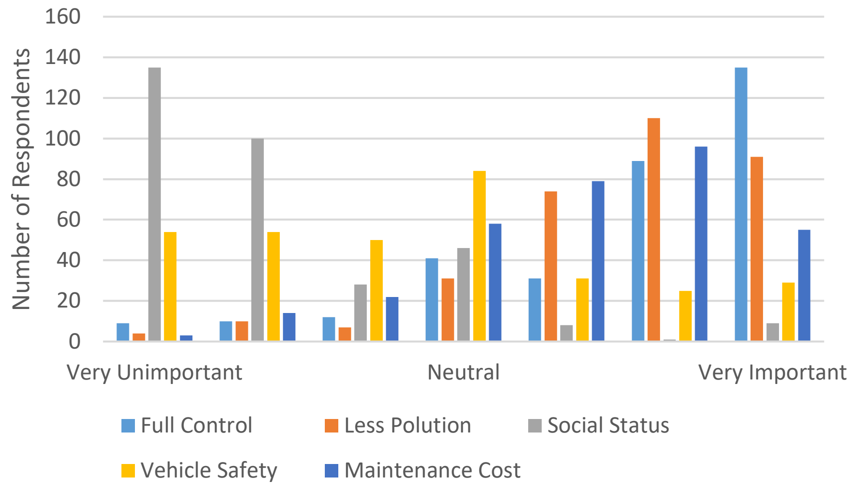

Figure 7 Perceived importance of CAV attributes (a)

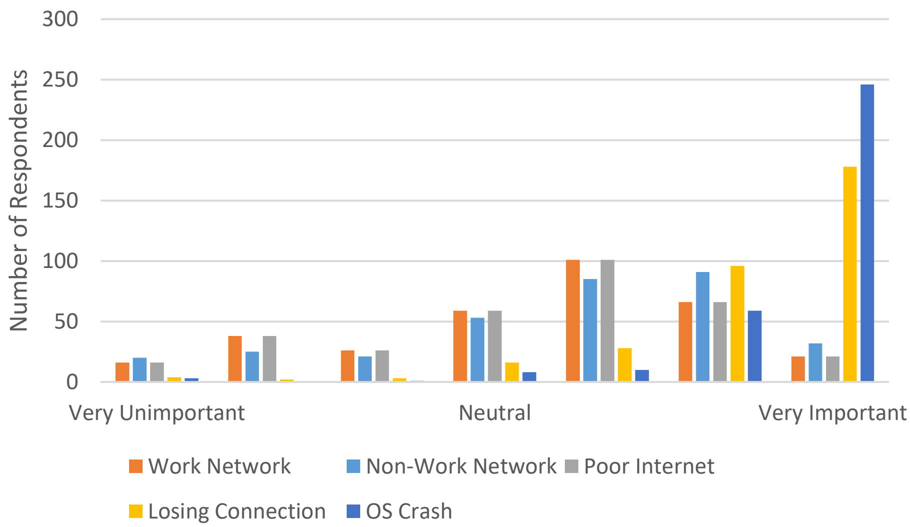

Figure 8 Perceived importance of CAV attributes (b)

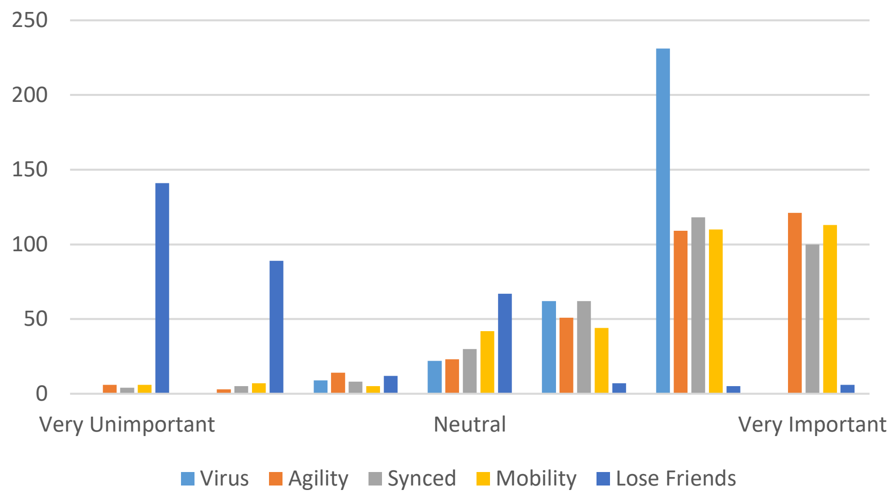

Figure 9 Perceived importance of CAV attributes (c)

The reported influence of a reduction in pollution and a change in social status matches with other data collected in the survey. Respondents were asked to rank the importance of various attributes of a vehicle such as the price and quality of a vehicle, environmental impact, and the effect the vehicle may have on their image. Unsurprisingly, the price and quality of the vehicle are the most important characteristics. Personal image is generally seen as unimportant, whereas the environmental impact of the vehicle is seen as somewhat important to potential buyers. Figure 10 shows this data below.

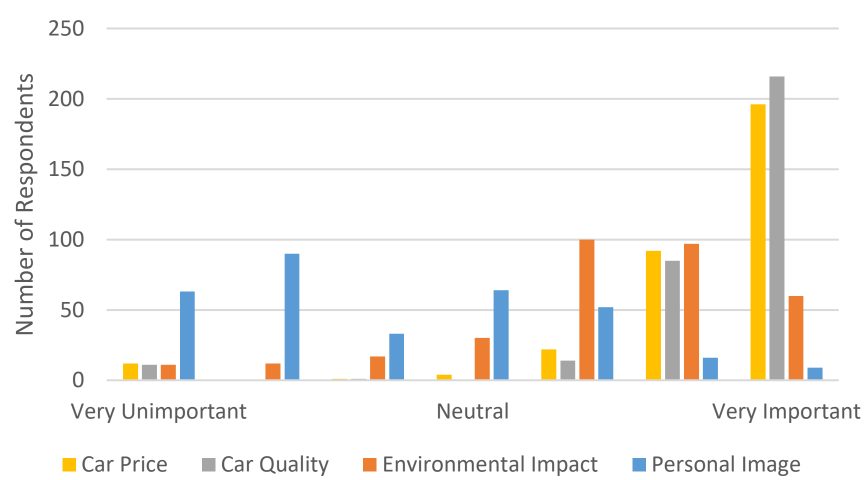

Figure 10 Perceived importance of vehicle attributes

Information on vehicle purchasing patterns was also gathered. The majority of respondents reported purchasing a vehicle every 5 or 10 years. When asked their intent to change vehicles over the next three years, the majority of respondents reported no changes, with buying a new vehicle and selling the current vehicle as a distant second option. This data is presented in Figures 11 and 12 below.

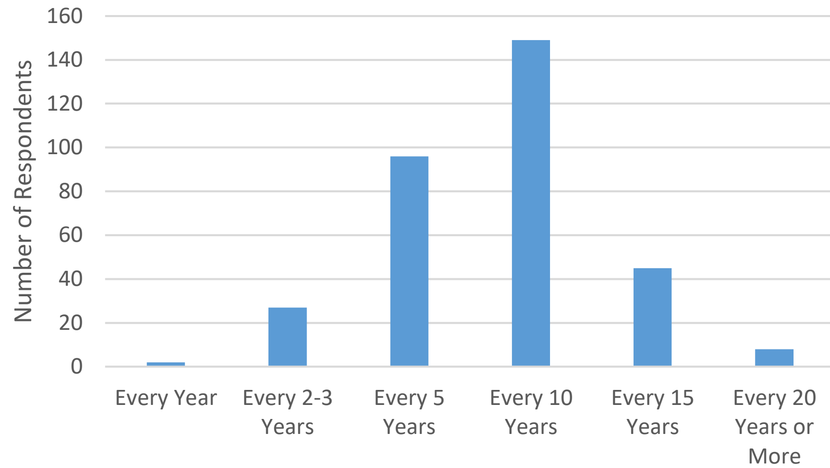

Figure 11 Frequency of vehicle purchases

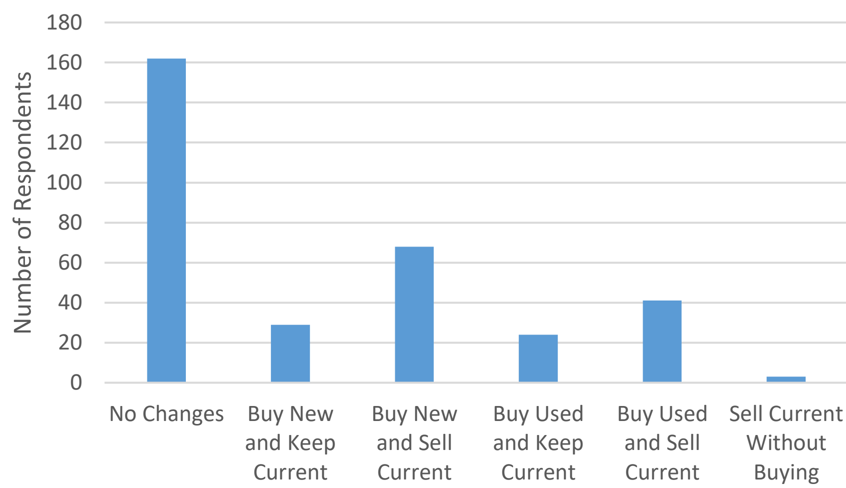

Figure 12 Intent to change vehicles in 3 years

The amount of money respondents are willing to pay for vehicles, CAV technology, and CAV maintenance was also gathered. Most individuals are unwilling to spend more than around $40,000 on a new vehicle, and few are willing to spend more than a few thousand dollars more on CAV technology. Many respondents reported that spending additional money maintaining a CAV system was not acceptable, although the majority of the responses indicate that a few hundred dollars would be a reasonable expectation. Figures 13-15 demonstrate this data.

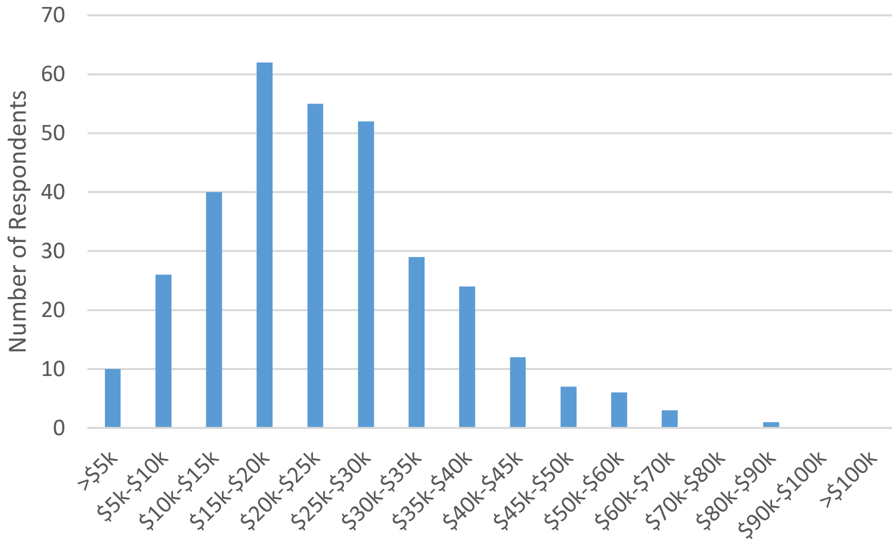

Figure 13 Willingness to pay for a vehicle

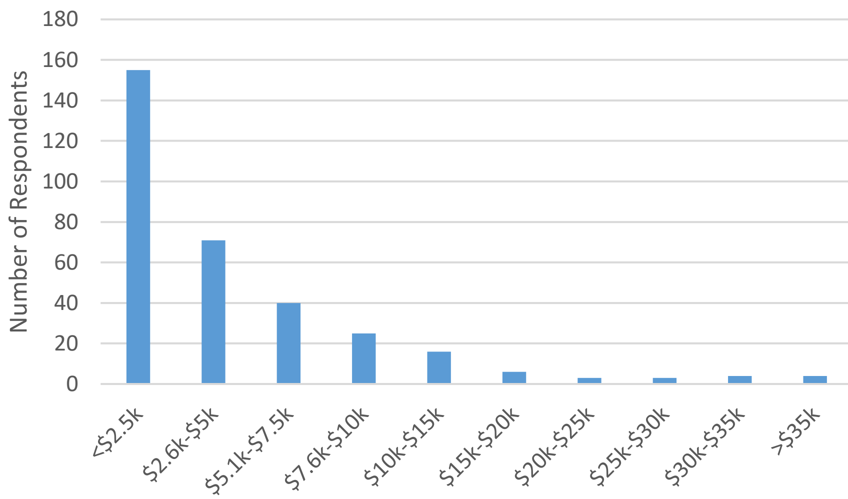

Figure 14 Willingness to pay for CAV technology

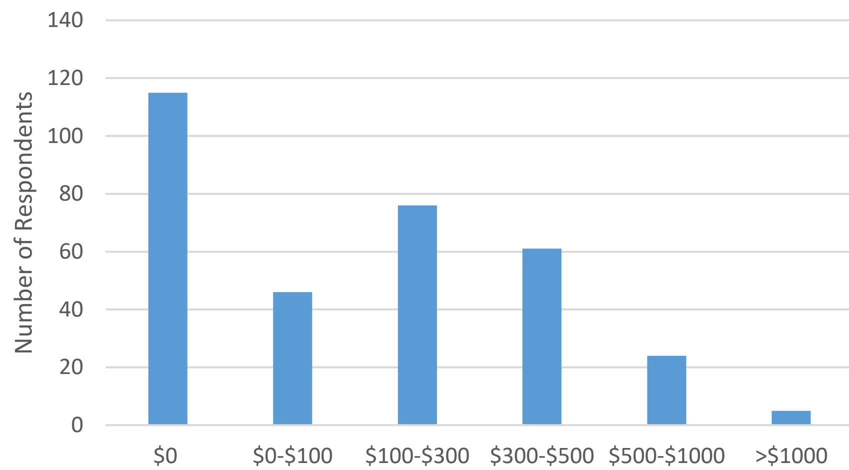

Figure 15 Willingness to pay for additional maintenance for CAVs

In addition to the seed data, we collected aggregate-level data on gender, ethnicity, college/division, age, and salary of the employees at the University of Memphis. The survey and marginal data are used in the population synthesis model to generate a synthetic population of the university employees. Figures related to this data can be viewed in the Appendix.

Given the synthetic network, the next step is to construct a synthetic network among the individuals. Recall that calculating the distance among agents requires the parameter ω_m which specifies the weight of each attribute of interest. These weights can substantially impact the structure of the network. Figure 16 shows the impact of the weight for division distance on network shape when all other weights are set to 1. As the weight increases, the tie selection algorithm pairs individuals within the department/division they are working, and the network takes the shape of small-world networks. For this preliminary study, we considered the values for X Y and Z weights as 2 and set other weights to 1. In a future project we will collaborate with the Department of Psychology at the University of Memphis to

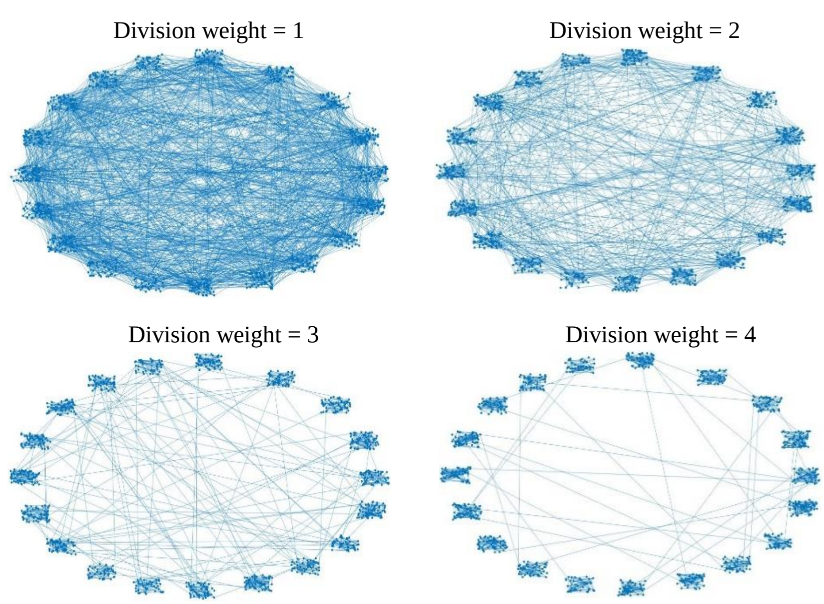

Figure 16 Effect of division weight factor on network structure

better understand how work and non-work social networks are formed, and incorporate the findings into the network synthesis model.

DISCUSSION AND CONCLUSION

Data from the survey indicate that social factors should be included into predictions of CAV market penetration rates. This also agrees with the literature regarding Diffusion of Innovations theory. Respondents are less concerned with how their peers will react to CAVs after adoption has occurred than they are concerned about how their peers feel about CAVs before adoption. The main concerns surrounding CAVs are safety-related, with mobility and maintenance costs close behind. Vehicle safety has been a major topic for decades, and CAV technology has the potential to be especially dangerous by removing control of the vehicle from the driver. Any uncertainty about the safety of the vehicle is of paramount importance to future consumers. The price, quality, and environmental impact of CAVs are also very important considerations for consumers. Since CAVs are not yet in full production, it is difficult to tell whether there will be a perceived drop in performance and quality for CAVs compared to traditional vehicles. CAVs are currently predicted to be more expensive, but less harmful to the environment. The increased price will prove to be a barrier for some potential adopters, but a majority of consumers are willing to invest a few hundred dollars for the technology. More research is needed including a survey in the study region to further develop adoption profile over time. However, methodology built in this research can be used along with the survey to develop CAV diffusion.

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APPENDIX

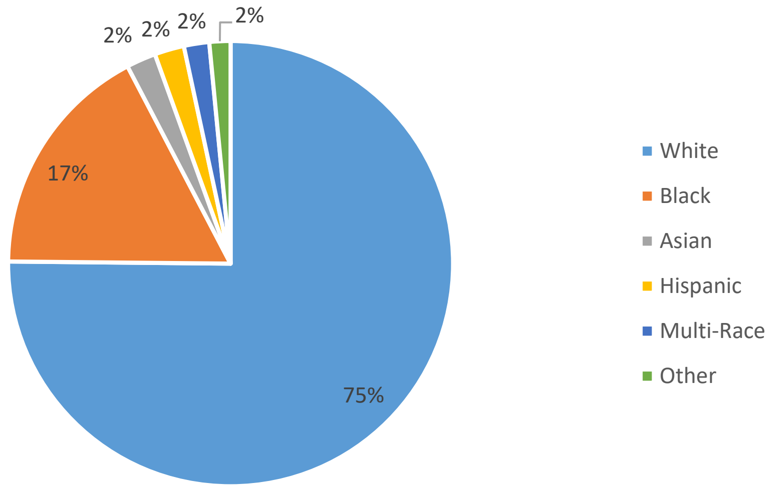

Figure 17 Racial composition of respondents

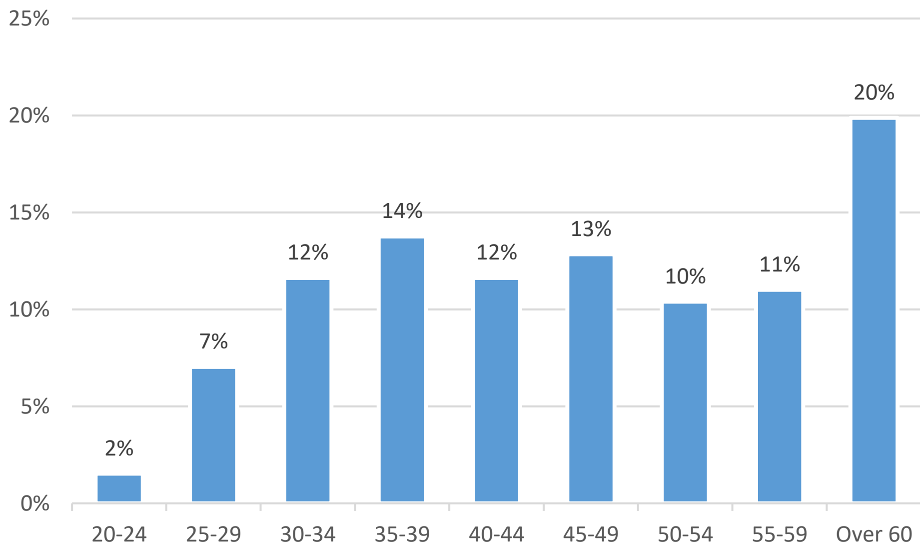

Figure 18 Age of respondents

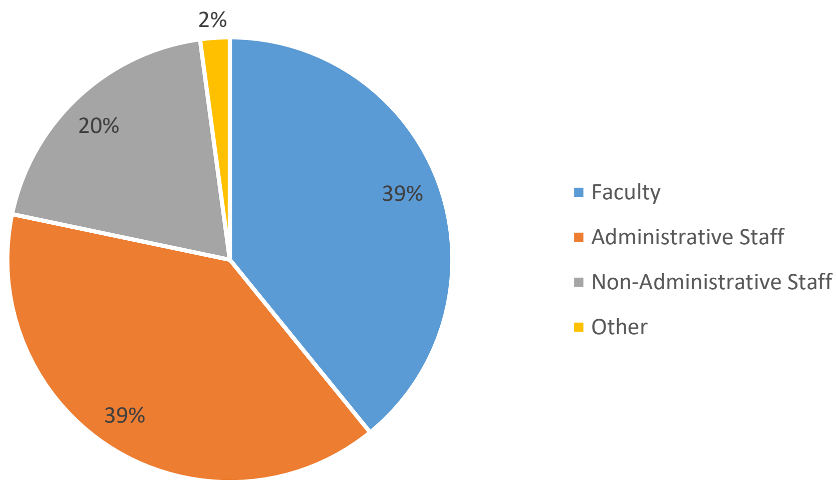

Figure 19 Employment type of respondents

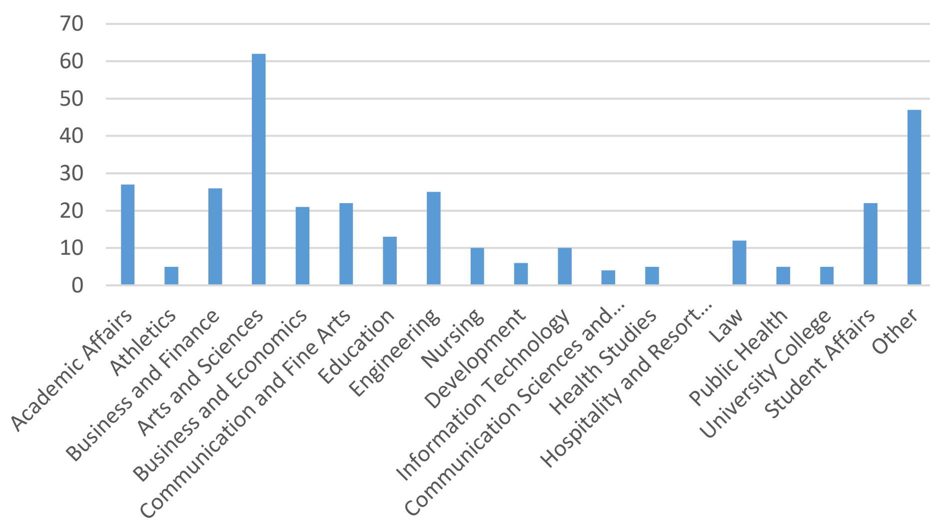

Figure 20 Respondents by department

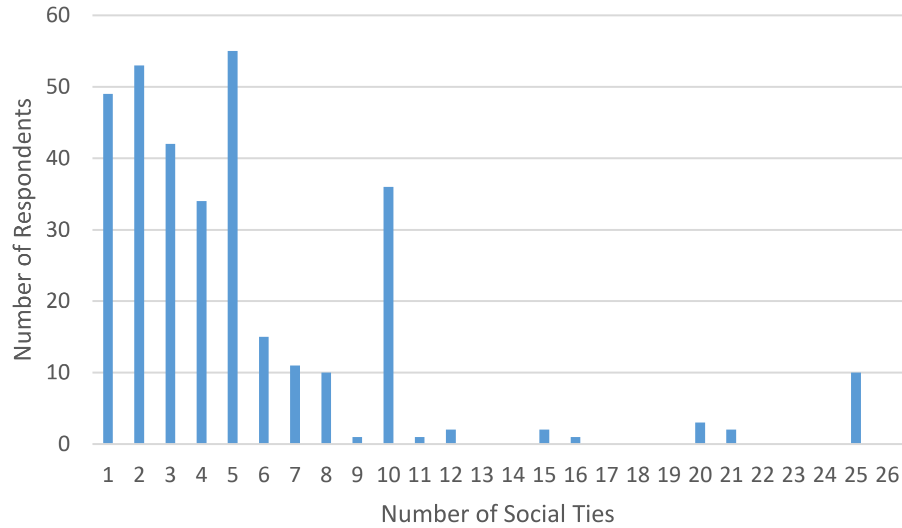

Figure 21 Number of social ties for respondents

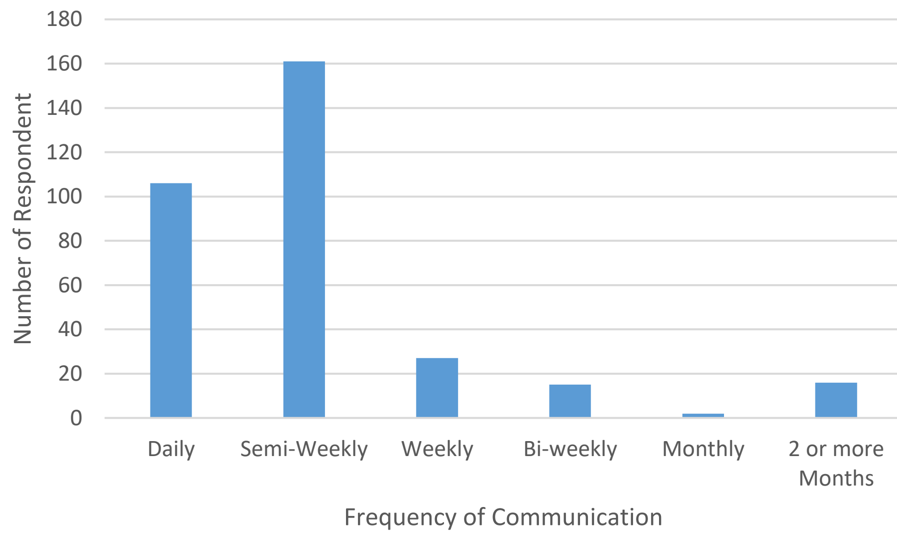

Figure 22 Frequency of communication for respondents

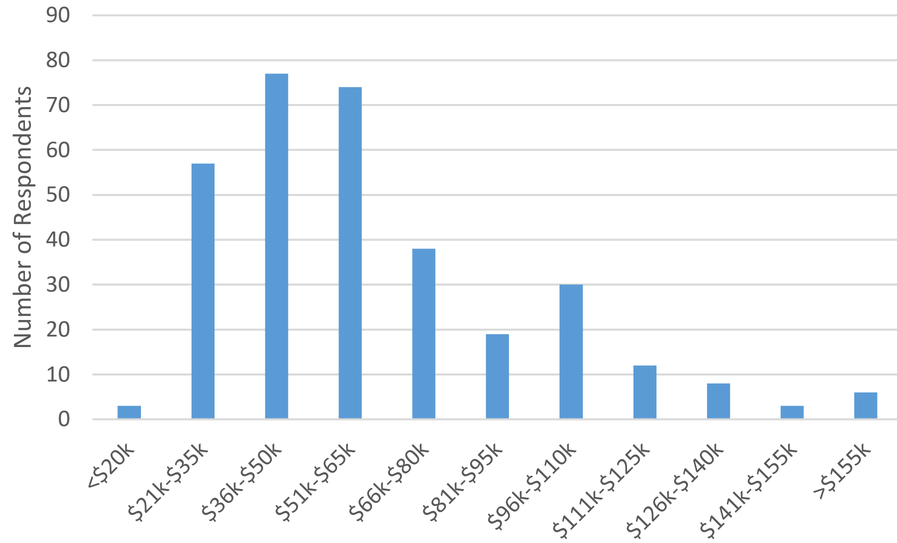

Figure 23 Respondent income level

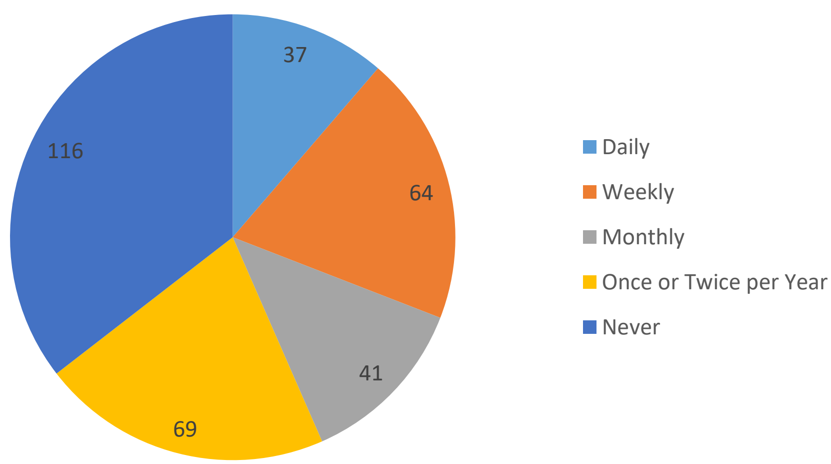

Figure 24 Frequency of telecommuting

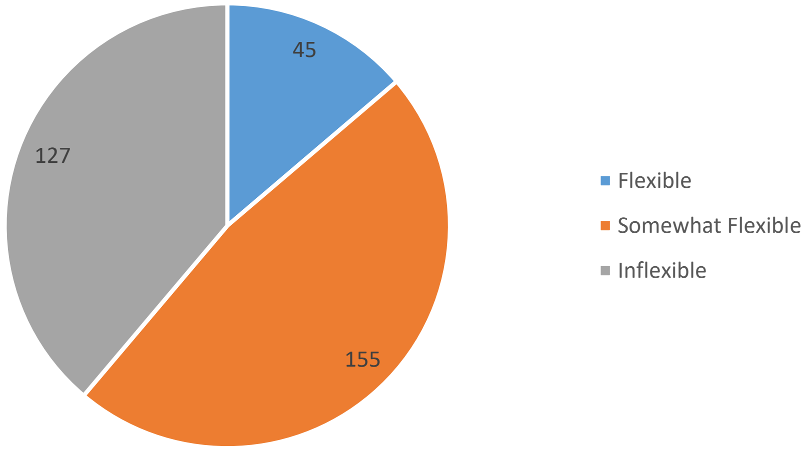

Figure 25 Flexibility of work starting time

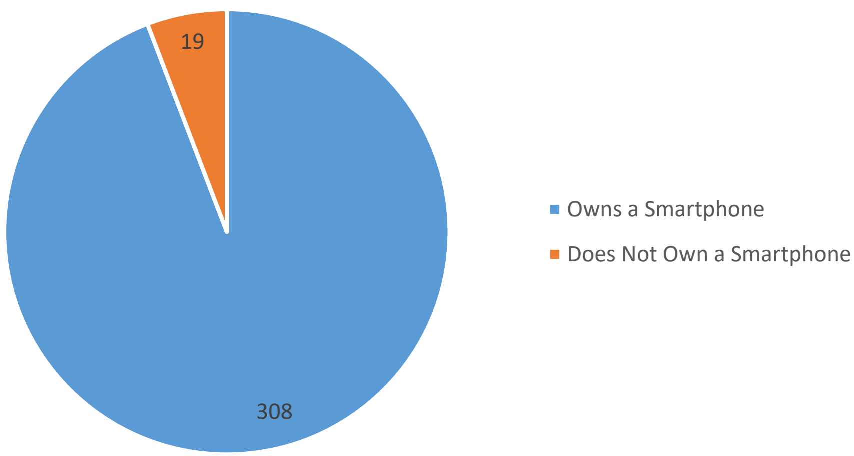

Figure 26 Smartphone ownership

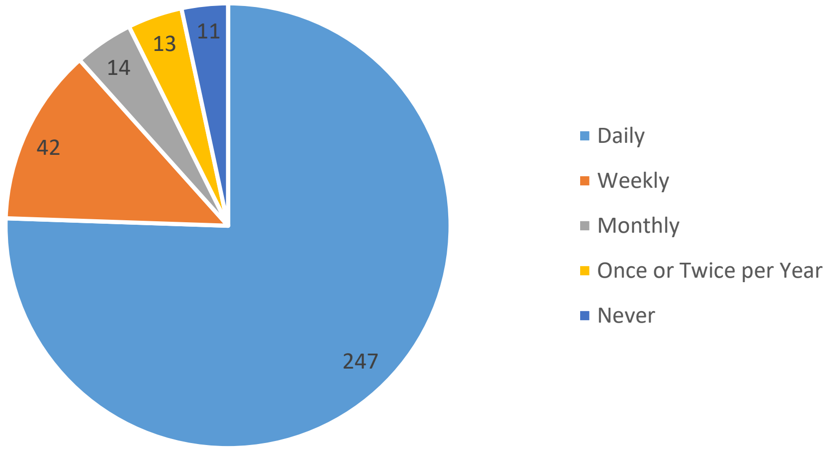

Figure 27 Frequency of radio use

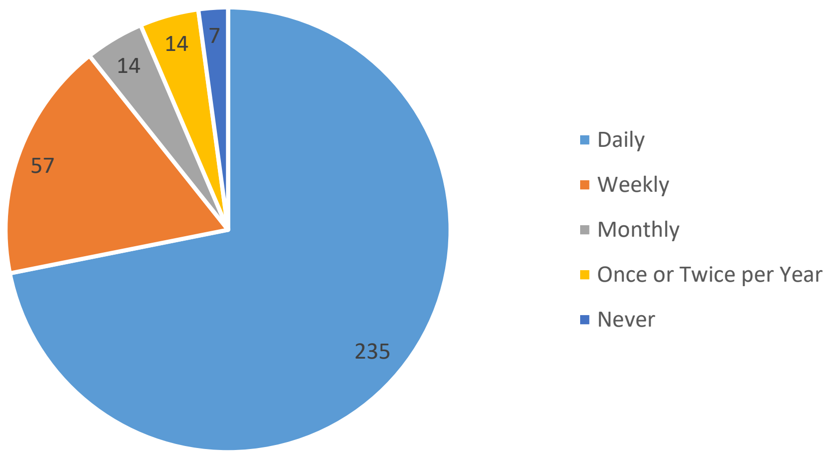

Figure 28 Frequency of TV use

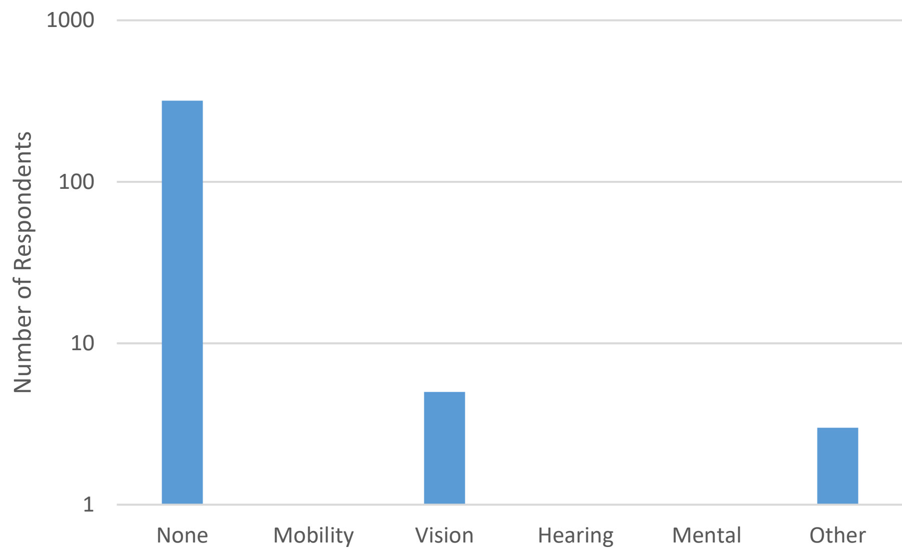

Figure 29 Disabilities of respondents

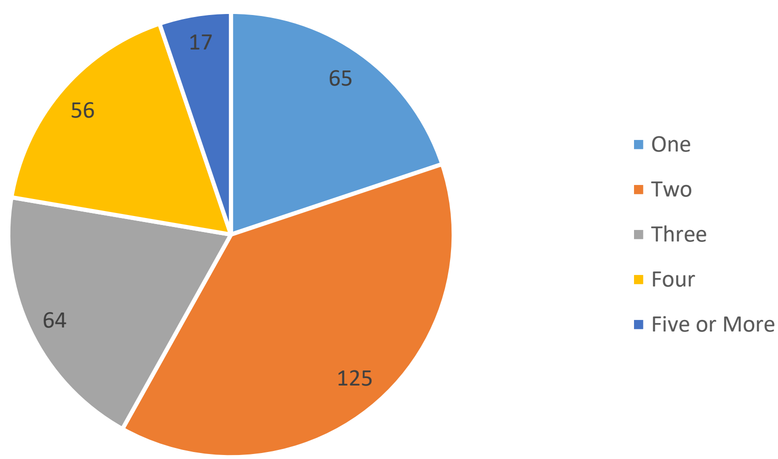

Figure 30 Household size

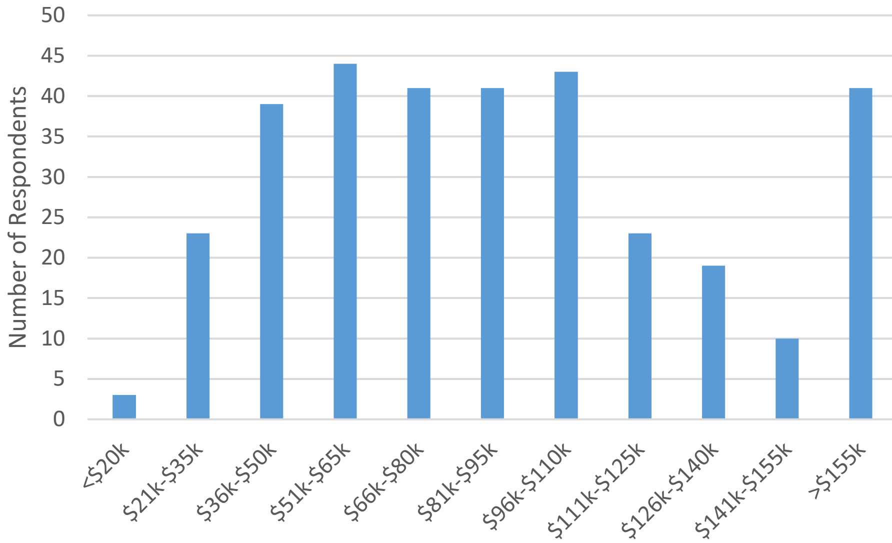

Figure 31 Household income

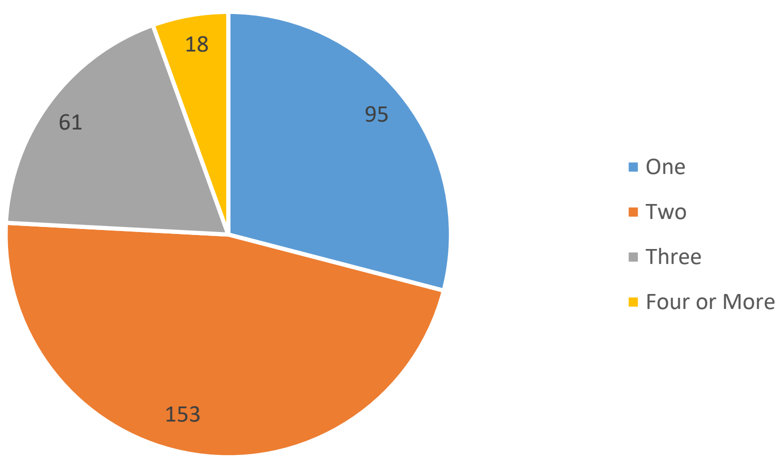

Figure 32 Household vehicle ownership