PREDICTING THE DEMAND FOR CONNECTED AUTONOMOUS VEHICLES: A NEW APPROACH BASED ON THE THEORY OF DIFFUSION OF INNOVATION

Ahmadreza Talebian [a,1], Sabyasachee Mishra[b]

[a] Department of Transportation Engineering, Isfahan University of Technology
Isfahan, Iran 84156-83111

[b] Department of Civil Engineering, University of Memphis
112D Engineering Science Building, Memphis, Tennessee 38152

Abstract

On the grounds that individuals heavily rely on the information that they receive from their peers when evaluating adoption of a radical innovation, this paper proposes a new approach to forecasting long term adoption of connected autonomous vehicles (CAVs). The concept of resistance is employed to explain why individuals typically tend to defer adoption of an innovation. We assume that there exists a social network among individuals through which they communicate based on certain frequencies. In addition, individuals can be subject to media advertisement (marketing) again based on certain frequencies. An individual's perceptions are dynamic and change over time as the individual is exposed to advertisement and communicates with satisfied and dissatisfied adopters. We also explicitly allow willingness-to-pay to change as a result of intercommunication. Applicability of the proposed approach is shown using a survey of employees of the University of Memphis. Our results show that the automobile fleet will be near homogenous in about 2050 only if CAV prices decrease at an annual rate of 15% or 20%. We find that a 6-month pre-introduction marketing campaign may have no significant impact on adoption trend. Marketing is shown to ignite CAV diffusion but its effect is capped. CAV market share will be close to 100% only if all adopters are satisfied with their purchases; therefore, the probability that an individual becomes a satisfied adopter plays an important role in the trend of adoption. The effect of the latter probability is more pronounced as time goes by and is also more prominent when CAV price reduces at greater rates.

Keywords

Connected autonomous vehicles; social network; diffusion of innovation; agent-based modeling; simulation; demand

[1] Corresponding author. Tel.: +98 31 33911406. E-mail: talebian@cc.iut.ac.ir

1. Introduction

Connected autonomous vehicles (CAVs) are about to become a reality, and they are arriving much earlier than many would think. By incorporating features such as parking assist, adaptive cruise control, and collision avoidance systems, most automobile manufacturers have already incorporated some degrees of automation into the existing cars. Also, Mercedes-Benz, Google, Tesla, and others have already developed and tested prototypes of the first fully autonomous vehicles. Because of these advancements, research on various aspects of CAVs has gained increasing attention over the past decade. While automobile manufacturers have made huge investments to make the technology more viable, affordable, and safer, academic efforts have been directed to issues such as safety (Alonso et al., 2011; Fagnant and Kockelman, 2015; Gurney, 2013; Kalra and Paddock, 2016; Liu and Khattak, 2016), congestion and traffic operations (Le Vine and Polak, 2016; Le Vine et al., 2017; Maciejewski and Bischoff, 2017; van den Berg, Vincent AC and Verhoef, 2016), travel behavior (Harper et al., 2016; Hohenberger et al., 2016; Truong et al., 2017), environmental impacts (Brown et al., 2014; Tsugawa et al., 2011; Wadud et al., 2016), and freight operations (Kunze et al., 2009; Kunze et al., 2011; Muratori et al., 2017).

One key question that has been of interest to policymakers, academic researchers, and industry professionals is *how much will be the demand for ownership of CAVs and how will be the timing of adoption in long-term*? Most of the recent studies with focus on the demand for CAVs address respondents' willingness-to-pay (WTP) as well as their opinions and concerns (Choi and Ji, 2015; Daziano et al., 2017; Haboucha et al., 2017; Kyriakidis et al., 2015; Lavieri et al., 2017; Menon et al., 2016; Pettersson and Karlsson, 2015; Schoettle and Sivak, 2014). On the other hand, a limited number of studies attempt to forecast evolution of connected autonomous fleet.

The majority of studies on adoption forecasting are based on expert knowledge, projection of adoption trends of other technologies, and sales estimates. Among the studies in the first category, a group of experts from the Institute of Electrical and Electronics Engineers (IEEE) suggest that about 75% of all vehicles will be CAVS by 2040 (IEEE, 2012). Bierstedt et al. (2014) forecast that the autonomous fleet will be in the range of 50%–75% between 2035 and 2045. Using future sale estimates, IHS Automotive (2014) determines that nearly all vehicles in use will be autonomous after 2050. Based on the adoption patterns of previous vehicle technologies such as navigation systems, air bags, and hybrid vehicles, Litman (2014) forecasts that in the most optimistic and pessimistic scenarios, CAVs will be 95% and 70% of vehicles in 2070, respectively. Different from the latter studies, Bansal and Kockelman (2017) develop a micro-simulation model to forecast long-term adoption of CAVs in the US. Multiple discrete choice models are used in a Monte Carlo simulation to emulate decisions such as buying or selling a car, purchasing a used or new car, adding connectivity and automation features. In three scenarios, the authors assume that individuals' WTP increase at the rates of 0%, 5%, and 10%, annually. The study suggests that the fleet of light-duty vehicles in the US will not be near homogenous by 2045.

Discrete choice modeling has been the prevailing approach in understanding various aspects of the demand for CAVs (Bansal and Kockelman, 2017; Haboucha et al., 2017; Lavieri et al., 2017; Liu et al., 2017; Menon et al., 2016). Choice models try to capture decision makers' preferences amongst a set of available alternatives. These models are based on the notion of stated preference which assumes that an individual's expectations are the same as market outcome; thus, stated preferences will remain valid. This assumption, known as rational expectations, could be problematic when a radical innovation, such as CAVs, is introduced to the market. In such a case, consumers have no previous experience on which they can base expectations (Snowdon et al., 1994). Empirical evidence suggests that individuals heavily rely on the information they receive from their peers when assessing adoption of a radical innovation (Henry, 2009; Wilson and Dowlatabadi, 2007). Discrete choice modeling fails to capture the effects that adoption of an individual may have on other individuals within his/her network.

One promising avenue to forecast the demand for the next generation of transportation fleet is the theory of Diffusion of Innovation (DOI). DOI theory seeks to understand how an innovation will diffuse as a result of communication and consumer interactions in a social network. DOI theory considers innovation diffusion as a social phenomenon which has four aspects: (i) the demand to adopt the innovation; (ii) communication through certain channels; (iii) communication among individuals in a social network; and (iv) communication over time (Rogers, 1976; Rogers, 2010). It should be noted that innovation is not limited to new technologies, but also includes new ideas and practices although in this paper we focus on the technological side (i.e., CAVs). Diffusion research has been of interest to the academic community for an extended period of time. The seminal diffusion study was published in 1943, when Ryan and Gross (1943) modeled the diffusion of hybrid seed corn among Iowa farmers. In 1969, the revolutionary paradigm of Bass (Bass, 1969) was introduced in which adoption is forecasted based on the number of previous adopters. The basic idea behind the Bass model is that mass communication (i.e., media) starts the diffusion of an innovation, and word-of-mouth (WOM) pushes it forward. The Bass model is based on a hazard function that describes conditional probability of adoption at each time point using two parameters: innovation and imitation coefficients. The Bass model was later extended by various researchers to account for issues such as multi-generation products (Mahajan and Muller, 1996; Michalakelis et al., 2010; Norton and Bass, 1987), pirated sales (Givon et al., 1995; Liu et al., 2011), and pricing strategies (Bass et al., 1994; Krishnan et al., 1999; Robinson and Lakhani, 1975). The Bass model is commonly used to reproduce diffusion of new products at an aggregate level, and its application for forecasting new products requires strong – and in some cases invalid – assumptions. For example, one may assume that the adoption pattern of CAVs will be similar to previous technologies (Lavasani et al., 2016), but historical data on adoption shows that each new product has its own distinct adoption pattern (Christiansen, 2008; Perry, 2010). Moreover, the Bass models neglect the micro-level impacts on adoption of social interactions.

This paper contributes to the literature by coupling the theory of DOI with agent-based modeling (ABM) context to forecast CAV adoption at a disaggregate level. Our modeling approach explicitly allows for communication among individuals, as a result of which perceptions about CAVs will be dynamic. Unlike previous studies assuming ad-hoc changes in willingness-to-pay, our approach let each individual's WTP positively or negatively alter due to communication with adopters who are satisfied or dissatisfied with their purchases. This construct is based on strong empirical evidence suggesting statistically significant impact on WTP of word-of-mouth (Parry and Kawakami (2015). Using a survey of the University of Memphis (UofM) employees, we show the applicability of the proposed approach. To this end, we first conduct multivariate normal imputation to fill-in the missing values of the survey data. Iterative Proportional Updating procedure is employed to inflate the sample data to the full population of UofM employees. Building upon the concept of *homophily*, which indicates that individuals with geographical proximity and socioeconomic similarity are more likely to be peered, we develop a synthetic social network among agents. Policy-relevant insights are offered by simulating CAV adoption over the period between 2025 and 2050.

The remainder of this paper is organized as follows. Section 2 elaborates the notion of resistance, a key concept in adoption modeling based on the theory of DOI. Section 3 presents the details of agent-based simulation of adoption. Section 4 discusses our survey design and key findings of the survey. Section 5 puts forward our approach to developing the social network among individuals. Section 6 offers numerical analysis and results discussions. Summary of major findings and directions for further research are given in Section 7.

2. Resistance Concept

Before delving into the agent-based framework of adoption modeling, let us elaborate the concept of resistance which is a fundamental notion in explaining adoption using DOI theory. Industrialized nations are recognized by advanced technological innovations. The question is that why then do individuals typically resist to some innovations? Automobile manufacturers certainly realize the benefits of automated features on vehicles but individuals do not see this new technology from that perspective. Consumers are typically resistant to innovations, especially revolutionary ones, as innovations can change their established routines and day-to-day existence. It is worth highlighting three aspects of consumer resistance. First, resistance can impact the timing of innovation adoption. The marketing literature categorizes consumers into five categories: innovators, early adopters, early majority, late majority, and laggards. Each group has a certain level of resistance, and the variations in resistance level influence adoption timing. Second, there exists a continuum of resistance: from passive resistance (inertia) to active resistance. Third, various classes of innovations (evolutionary and revolutionary innovations) cause different levels of resistance as they conflict with the consumers' routines differently.

In this study we consider nine aspects for resistance toward CAV adoption. Following Ram and Sheth (1989) and Zsifkovits and Günther (2015), these resistances (barriers) are segmented into two categories:

1. <u>Functional barrier:</u> arises when the innovation challenges an individual's current workflows and habits. Three subcategories can be identified:
    a. *Product usage patterns*: this is realized when the innovation is incompatible with the existing practices. Inability to use autonomous features in areas with low internet coverage is one aspect of usage barrier.
    b. *Product value*: some consumers will adopt only if the ratio of performance over value for CAVs is greater than that for traditional cars. We incorporate willingness-to-pay into our modeling approach to account for product value barrier.
    c. *Risks*: this barrier is induced when the users have uncertainty about the *actual* consequences of adoption. Risk of malfunctioning due to operating system crash, virus attack, or disconnection from internet are three aspects of usage risk barrier. Economic risk relates to the fear of higher than expected maintenance costs.
2. <u>Psychological barrier</u>: arises when there are conflicts with the consumers' prior beliefs. Two sub-categories for psychological barrier are:
    a. *Traditions and norms*: this is realized because CAVs will change consumers' 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, this notion that a computer system will have full control of the automobile can hinder them from adoption. Another aspect of tradition barrier pertains to safety that is people feel that CAVs may not be as safe as traditional cars.
    b. *Perceived product image (image barrier)*: the difference between the product's image and the consumer's perception leads to a barrier obstructing adoption. For example, consumers preferring sport cars may imagine that CAVs are less agile and maneuverable than traditional cars.
    c. *Risk*: Losing or lessening relationship with friends who are not willing to purchase CAVs is an example of psychological risk. This risk specifically relates to social circles with aggressive driving behavior.

We also recognize four dis-barriers (incentives) for CAV adoption. First, CAVs can be synched with traffic signals and other vehicles to lower travel time and cost. This can be viewed as a functional dis-barrier. Second, having a CAV can improve one's status among his/her peers. This incentive is the opposite of image barriers. The third incentive pertains to environment as CAVs can use real time traffic information in order to efficiently navigate to their destination and thus generate less pollutants. This incentive may not be considered as an important motive of purchase for less environmentally conscious consumers. Fourth, CAVs can provide a greater degree of mobility to consumers with impairment.[2]

[2] The terms *agent*, *consumer*, and *individual* are used interchangeably throughout the text.

As the number and intensity of resistances realized by an individual increase, she/he starts to defer adoption. Two factors can impact the individual resistances and incentives and facilitate the adoption process (Ram, 1987; Ram and Sheth, 1989; Wangenheim, 2005):

1. Mass communication (marketing): media advertisement can target a broad spectrum of consumers to reduce both functional and psychological barriers. Marketing, for example, can weaken tradition barrier by convincing consumers that they can take the full power of their vehicles at any time. The marketing literature suggests that in adoption of a radical innovation, marketing can reduce resistances to a limited extent and is mostly effective at the early stages of adoption.
2. Peer-to-peer communication (word-of-mouth): once individuals received initial information through media advertisement, the information that propagates among peers will be the main propeller of diffusion. Communication between satisfied and potential adopters strengthens incentives and weakens barriers. Communication occurs within a social network in which nodes represent individuals and communication channels are shown using directed arcs. The frequency and intensity of communication between a pair of individuals determine how effective a communication channels is. For example, some individuals talk to others more frequently and some are more communicative; thus there will be a greater influence on the potential adopters from more socialized adopters (Günther et al., 2011). The pattern of information diffusion largely hinges upon the way the network is structured. More specifically, position of a specific individual in the network can be such that his/her level of uncertainty about adoption decreases faster than other individuals (Abrahamson and Rosenkopf, 1997).

3. Agent-Based Simulation Modeling of DOI

This section presents the agent-based framework that models the process in which peer-to-peer communication and media advertisement impact the determinants of adoption decision, i.e., resistances and incentives. This framework consists of three components: (i) mass communication; (ii) pre-introduction vehicle purchase; and (iii) peer-to-peer communication. In what follows, we describe each component in detail. These components assume that a set of individuals and the corresponding social network is given. Later in Section 5, we discuss how such set and network can be developed using survey data.

Component 1: Mass communication model

As discussed previously, an individual's decision to whether or not purchase a product largely depends on how he/she perceives the product's various aspects. Perceptions are dynamic and may change over time as the individual communicates with his/her peers and is exposed to media advertisement. Specifically, individuals watching TV or listening to radio are exposed to advertisement, and the impact of advertisement is a function of frequency of exposure.[3] We consider two marketing stages: pre-introduction and post-introduction. We assume that car manufacturers initiate marketing campaigns at a certain time point before introduction of CAVs to possibly attract a greater number of innovators. We reasonably assume that agents have memory and the effect of advertisement accumulates over time, but also dissipates as time goes by. Let $X_{i,l}^{t}$ denote the l^{th} element of agent i's perception about CAVs at time t. This perception is dynamic and is updated according to $X_{i,l}^{t} = X_{i,l}^{t-1} + y_i^{t,t-1} \frac{X_{i,l}^{t}\tau_{i,l}}{(1+\rho)^{f_i^{t-1}}}, \forall l \in L, t = 1,2, \dots, T, i \in I$, where I is the set of agents, L the set of perception elements, $y_i^{t,t-1}$ a binary variable equating 1 if agent i has been exposed to advertisement between $t-1$ and t, $\tau_{i,l}$ a stochastic scalar between 0 and 1 indicating the impact of

[3] Our survey of UofM employees, which will be discussed later, shows that 75.7% of respondents listen to radio and 71.9% of them watch TV on a daily basis. 12.8% and 17.4% of employees state that they listen to radio and watch TV once a week or more. Only 2.1% and 3.4% of respondents never watch TV and listen to radio. We should reasonably expect considerable exposure to media advertisement.

one round of advertisement on agent i's l^{th} element of perception, ρ dissipation rate of advertisement impact, and f_i^t the total number of times that agent i has been exposed to advertisement until time t. Mass communication changes one's perception about CAVs through the same mechanism in pre- and post-introduction stages but at different rates (i.e.,, $\tau_{i,l}$ can be different in pre- and post-introduction stages).

Component 2: Pre-introduction vehicle purchase model

Following Shafiei et al. (2013), we assume that vehicles' lifetime is drawn from a truncated normal distribution. Let LF_i denote vehicle's life for agent i. To determine a vehicle's life in the base year (Age_i^0), one can draw an age from the uniform distribution $U(0, LF_i)$, as suggested by Shafiei et al. (2012). By doing so, however, some agents who frequently purchase a car may get a car whose age is greater than the maximum age that corresponds to the agent's frequency of purchase. To address this issue, we develop a pre-introduction vehicle purchase simulation model. The steps of the algorithm are detailed below, where T_P denotes the length of pre-introduction vehicle purchase (warm-up) simulation.

Algorithm 1: The selection algorithm that develops social network among individuals

Stage 1

Step 0 (initialization): Set $t = 0$. For each agent $i \in I$, draw LF_i from truncated normal distribution $N(\mu, \sigma)$ with $Max = \bar{m}$ and $Min = 0$. Then, draw the vehicle age at the base year (Age_i^0) from $U(0, LF_i)$.

Step 1: Set $= t + 1$. $Age_i^t = Age_i^{t-1} + 1, \forall i \in I$.

Step 2: For each agent $i \in I$, if $Age_i^t > LF_i$ *or* vehicle purchase frequency stipulates a purchase, consider a vehicle purchase for agent i. Set $Age_i^t = 0$ and draw a new LF_i.

Step 3: if $t < T_P$, go to Step 1, otherwise terminate and report $Age_i^{T_P}$ as the algorithm's output.

Component 3: Peer-to-peer communication model

The information received from peer-to-peer communication significantly impacts purchase decisions (Baxter et al., 2003; Brown and Reingen, 1987; Mourali et al., 2005). The literature suggests that this information is two to seven times more effective than that received from advertisement in newspaper, radio, or magazines (Katz and Paul, 1966). To model intercommunication impacts, we follow Günther et al. (2011) and assume that there exists a learning process between a potential adopter and other adopted agents. Each agent i communicates with agents within its social network according to a certain frequency. The social learning impact on agent i is given by $X_{i,l}^t = X_{i,l}^{t-1} + \sum_{j \in E_i} z_{ij}^t \frac{w_{ij} \beta_{ij}^l (X_{i,l}^{t-1} - X_{j,l}^{t-1})}{(1+\alpha)^{fw_{i,j}^t - 1}}$, where E_i is agent i's set of adopted peers, z_{ij}^t dummy variable indicating if agents i and j communicated between time t-1 and t, β_{ij}^l a stochastic scalar representing the effect of communication with agent j on l^{th} element of agent i's perception (learning factor), fw_i^t the total number of times that agent i has had communication with agent j until time t, α the dissipation rate of WOM, and w_{ij} the weight of the social tie between agents i and j (see Section 5.2 for the latter).

Some adopted agents may not be satisfied with performance and features of CAVs, and thus start to propagate negative WOM. Behavioral research indicate that a dissatisfied consumer talks to more individuals, compared to a satisfied consumer (Anderson, 1998; TARP, 1982). Moreover, the power of negative WOM is known to be at least two times greater than positive WOM (Goldenberg et al., 2007). In this paper, we assume that both types of WOM can be transmitted among agents. This is modeled by manipulating the value of β_{ij}^l. When there is negative WOM between two agents, β_{ij}^l will be equal to (-1), multiplied by relative effect of negative WOM, multiplied by the value of β_{ij}^l corresponding to positive WOM. The literature frequently assumes that a fixed portion of consumers (e.g., 5% (Amini et al. 2012; Goldenberg et al., 2007)) are dissatisfied with their purchases. To account for stochasticity of this portion, we assume that there is a probability θ_2 that agent i becomes a dissatisfied adopter at the time of purchase. At each time t, we also assume that each satisfied adopter turns to a dissatisfied adopter with a probability θ_1. While conducting simulation, we make sure that a dissatisfied adopter never purchases a CAV in the next possible rounds of purchase. Nonetheless, such agent continues to spread negative WOM. On the other hand, a satisfied adopter continues with CAVs in the next possible purchases.

Empirical evidence indicates that communication with a satisfied(dissatisfied) adopter can increase(decrease) WTP (Parry and Kawakami, 2015). To account for this, we let WTP at each time point be determined by $WTP_i^t = WTP_i^{t-1} + \sum_{j \in E_i} \frac{w_{ij}\gamma_{ij}(WTP_j^{t-1} - WTP_i^{t-1})}{(1+\alpha)^{fw_{i,j}^t - 1}}$, where γ_{ij} is a stochastic scalar that captures the effect of communication with agent *j* on agent *i*'s WTP.

Figure 1 shows how the three modeling components are coupled to forecast diffusion of CAVs. The simulation model receives vehicle ages and individual perceptions at the introduction time from pre-introduction vehicle purchase and mass communication models, respectively. Based on the age of the existing vehicle and its automobile purchase behavior, each agent *i* makes a decision to whether or not purchase a new vehicle. An individual seeking to purchase an automobile is termed "*potential buyer*". At each time period t, each agent *i* has a total perception index (PI_i^t) which is equal to a weighted sum of barriers and incentives about CAVs: $PI_i^t = \sum_{l \in L} \varphi_l X_{i,l}^t$, where φ_l is the weight of the l^{th} element of perception. If agent *i* is a potential buyer, it first evaluates if it can afford a CAV, i.e., if its WTP is greater than the price of adding automation and connectivity at time t. If WTP_i^t is greater than the cost of adding automation, agent *i* compares total perception indexes against a cut-off value (PI_C) and decides whether it wants to purchase a CAV. The cutoff value is assumed to remain constant over time. Once each agent's purchase decision is determined, we update perceptions and WTP based on media exposures and peer-to-peer communications between t-1 and t, and proceed to time interval t+1. This process continues until time period T.

4. Survey Design and Results

We conduct a survey to (i) understand how individuals rely on various sources of information when they assess CAV adoption; and (ii) to develop a seed for generation of synthetic population. The survey consists of 41 questions that are grouped into four blocks. The first block of questions is about socioeconomic characteristics of respondents. The second block questions about household characteristics of the individuals. Vehicle purchase behavior, household WTP, and household income are among the questions that are asked here. The third block aims to discover information about the work social network that each individual has developed. Finally, the fourth block quantifies various resistances and incentives that individuals realize.

The Division of Research and Sponsored Programs at the University of Memphis processed the survey and determined that it is exempt from Institutional Review Board (IRB) review (IRB number: PRO-FY2017-598). 2,465 full-time employees of the University of Memphis were contacted through email and asked to complete the survey. In total, we received 327 complete responses (13.3%) which is a promising rate of response in the transportation field.

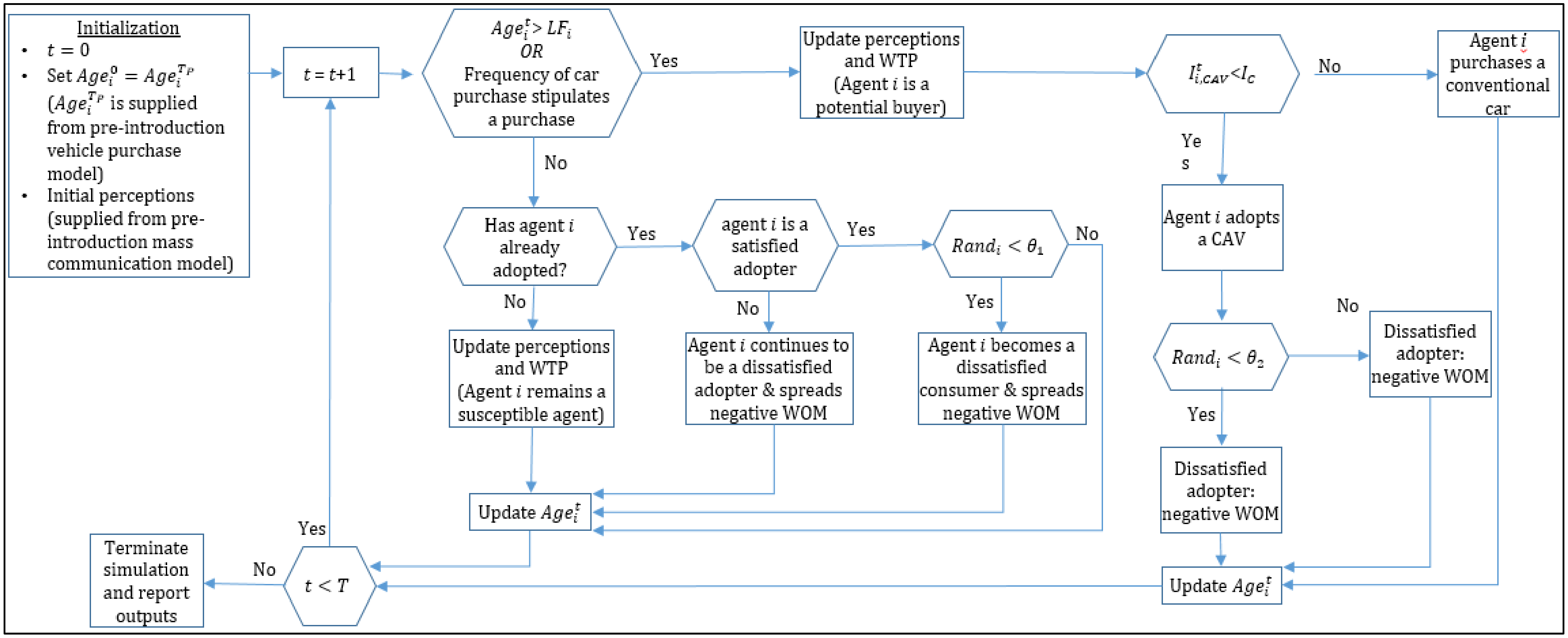

Figure 1: Simulation model for modeling adoption of CAVs

Of 15,369 entries (327 rows by 47 columns), 100 cells were missing, that is a missing rate of 0.65%. In order to fill-in missing values, we perform multivariate normal imputation using the R package Amelia II (Honaker et al., 2011). Multivariate normal imputation revolves around the idea that the distribution of the dataset, including both observed and missing entries, is multivariate normal (see Honaker and King (2010) for a detailed description of multivariate normal imputation methodology). We impute m values for each missing cell, and then use the average of the m values as the final filled-in value for the missing entry. In this study we set m=10 although Honaker et al. (2011) suggest that m=5 is also sufficient for low missing rates. To check the plausibility of imputation, we compare the distribution of imputed values to that of observed values. Overall, density comparison shows acceptable quality of imputation. For demonstration, density comparison for employment type (faculty/administrative staff/ non-administrative staff/other) and household income are presented in **Error! Reference source not found.**. In both panels, the relative density of modal imputation follows that of observed values to an acceptable extent.

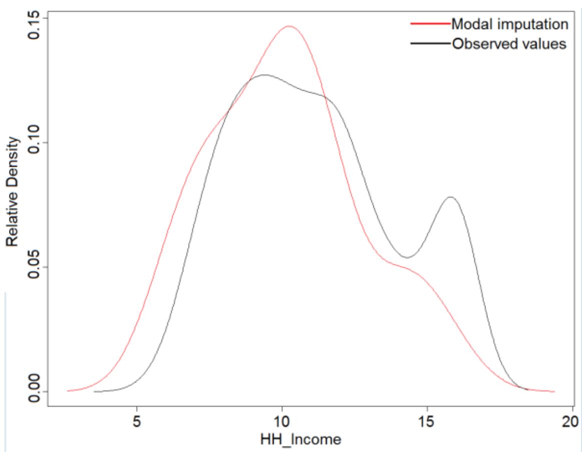

Figure 2: Density comparison for household income (HH_Income) and employment type (Employment)

Descriptive statistics of the survey results are presented in Table 1. Majority of respondents (63.3%) are female. In terms of race, 92% of respondents are either white or African American (or black). More than two third of respondents make less than $65,000 annually. We observe that the respondents are relatively equally scattered across the six intervals representing the ages of 30 to 60 years. We expected to receive a small number of responses from non-administrative staff, mainly because of the nature of their job which may not require regular use of computer and email. Fortunately nearly 20% of respondents were non-administrative staff. In this study we assume that household is the entity making the decision to purchase a new car, and thus household income and WTP affect adoption. Only two respondents stated they purchase a car annually. On the other hand, 29.4% of them purchase a car every five years and 45.6% make a car purchase every 10 years. In total, less than 5% of respondents state that their households are willing to pay an additional $20,000 to add automation and connectivity. 69.1% of respondents' households are willing to pay only an additional $5,000 or less to have the driverless option added to their car. On a seven-point scale (1 = *Very Unreliable* to 7 = *Very Reliable*), individuals consider an average reliability score of 5.58 ($\sigma = 1.08$) for the information they receive from their peers, while the scores for media and car dealership are 3.79 ($\sigma = 1.36$) and 3.63 ($\sigma = 1.44$), respectively. This highlights the necessity of incorporating WOM into adoption modeling. Individuals give relatively equal weights to the information they receive from their work and non-work social network; it is therefore reasonable to assume that the information received through work social network can effectively change individuals' decision regarding CAV purchase. On average, individuals have five peers. Most individuals (94.5%) talk about non-work materials with their peers at least once a week. We identify nine barriers and four incentives form an individual's perception. Individuals are asked to rate their opinion about each barrier/incentive on a seven-point scale (1 = *Strongly disagree* to 7 = *strongly agree*). Among respondents, risk of virus attack is considered as the most important barrier, with the highest average and lowest standard deviation ($\mu = 6.54$ and $\sigma = 0.91$). Respondents rated improving social status among peers as the least important incentive with $\mu = 2.18$ and $\sigma = 1.41$.

Table 1: Descriptive statistics of the survey results (after imputation dataset)

Variable	Level	Frequency	Variable	Level	Frequency
Gender			*Age*		
	Male	120 (36.7%)		<20	0 (0%)
	Female	207 (63.3%)		20-24	5 (1.5%)
Employment type				25-29	23 (7.0%)
	Faculty	128 (39.1%)		30-34	39 (11.9%)
	Administrative staff	128 (39.1%)		35-39	45 (13.8%)
	Non-administrative staff	64 (19.6%)		40-44	38 (11.6%)
	Other	7 (2.1%)		45-49	42 (12.8%)
Income				50-54	34 (10.4%)
	<$20,000	3 (0.9%)		55-59	36 (11.0%)
	$21-000-$35,000	57 (17.4%)		>60	65 (19.9%)
	$36,000-$50,000	77 (23.5%)	*Race*		
	$51,000-$65,000	74 (22.6%)		White	245 (74.9%)
	$66,000-$80,000	38 (11.6%)		African American or Black	56 (17.1%)
	$81,000-$95,000	19 (5.8%)		American Indian or Alaska native	1 (0.3 %)
	$96,000-$110,000	30 (9.2%)		Asian or Pacific Islander	7 (2.1%)
	$111,000-$125,000	12 (3.7%)		Hispanic or Latino	7 (2.1%)
	$126,000-$140,000	8 (2.4%)		Multi-race	6 (1.8%)
	>$141,000	9 (2.7%)		Other	5 (1.5%)
Household size			*Car purchase frequency*		
	1	65 (19.9%)		Once a year	2 (0.6%)
	2	125 (38.2%)		Once every 2-3 years	27 (8.3%)
	3	64 (19.6%)		Once every 5 years	96 (29.4%)
	≥4	73 (22.3%)		Once every 10 years	149 (45.6%)
WTP for adding automation & connectivity				Once every 15 years	45 (13.8%)
	<$2,500	155 (47.4%)		Once every 20 years and more	8 (2.4%)
	$2600-$5,000	71 (21.7%)	*WTP for CAV maintenance (in addition to regular cost)*		
	$5,100-$7,500	40 (12.2%)		$0 more	115 (35.2%)
	$7,600-$10,000	25 (7.6%)		Less than $100	46 (14.1%)
	$10,100-$15,000	16 (4.9%)		$100-$300	76 (23.2%)
	$15,100-$20,000	6 (1.8%)		$300-$500	61 (18.7%)
	$20,100-$25,000	3 (0.9%)		$500-$1,000	24 (7.3%)
	$25,100-$30,000	3 (0.9%)		>$1,000	5 (1.5%)
	$30,100-$35,000	4 (1.2%)			
	>$35,000	4 (1.2%)			
Reliability of information received from			*Frequency of communication with peers*		
	Social network:	$\mu = 5.57, \sigma = 1.09$		Once or more in couple of weeks	309 (94.5%)
	Media:	$\mu = 3.79, \sigma = 1.36$		Once a month	2 (0.6%)
	Car dealers:	$\mu = 3.63, \sigma = 1.45$		Once every few month	16 (4.9%)
Number of social ties			*Reliability of information received from*		
	$\mu = 5.27, \sigma = 5.045$			Work social ties	$\mu = 4.45, \sigma = 1.58$
	$Min = 0, Max = 25$			Non-work social ties	$\mu = 4.71, \sigma = 1.64$

Barriers	The autonomous feature does not work in areas with poor internet connection	$\mu = 6.02, \sigma = 1.40$
	There is a risk associated with losing internet connection (quitting self-driving mode)	$\mu = 6.25, \sigma = 1.12$
	There is a risk associated with crashing the operating system of CAVs	$\mu = 6.62, \sigma = 0.87$
	There is a risk associated with virus attack against the operating system of CAVs	$\mu = 5.82, \sigma = 1.33$
	There is a risk associated with higher annual maintenance costs for CAVs	$\mu = 5.15, \sigma = 1.39$
	CAVs might not be as agile as traditional cars while on autonomous mode	$\mu = 6.02, \sigma = 1.40$
	A computer will have full control over my car	$\mu = 5.70, \sigma = 1.56$
	By having a CAV, I may lose some friends who are not likely to purchase CAVs	$\mu = 2.23, \sigma = 1.46$
	A self-driving car might not be as safe as a standard car	$\mu = 3.53, \sigma = 1.81$
Motives	A CAV can provide a greater degree of mobility for someone with impairment	$\mu = 5.73, \sigma = 1.37$
	Having a CAV can improve my status among my peers	$\mu = 2.18, \sigma = 1.41$
	CAVs may generate less pollutants compared to traditional cars	$\mu = 5.61, \sigma = 1.31$
	CAVs can be synced with traffic lights and other vehicles to decrease travel time	$\mu = 5.74, \sigma = 1.25$

5. Social Network Development

5.1 Synthetic Population

A primary input for any agent-based model is a set of individuals. Collecting a fully disaggregate dataset through survey is usually costly, especially when a large population is of interest. Moreover, if collected, using such a dataset can be problematic in many countries due to strict privacy regulations. An alternative is to use aggregate data about the true population to generate an artificial population, thereby generating a synthetic population. Assume that the sample data provides the distributions of a set of attributes for agents, referred to marginal distributions. To develop a joint distribution, one can multiply the marginal distributions 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). Thus, there is a need for more sophisticated approaches of population synthesis. In general, there exist two approaches to generate a population of synthetic agents: synthetic reconstruction (SR) techniques and combinatorial optimization (CO) methods (Barthelemy and Toint, 2013). The CO approach partitions the area of interest into a number of zones. The approach requires a set of marginal distributions to be available for the attributes of interest. It then fits a sample of population to the set of margins for each zone. The SR methods, which are more common than CO, typically generate a joint distribution from marginal distributions and then sample from it. Researches have attempted to address issues affecting the quality of population synthesis through synthetic reconstruction such as simultaneous control of the individual and household variables (Arentze et al., 2007; Auld and Mohammadian, 2010; Guo and Bhat, 2007) and data limitations (Barthelemy and Toint, 2013; Farooq et al., 2013; Zhu and Ferreira, 2014). In this paper, we use an SR approach that employs the Iterative Proportional Updating (IPU) algorithm to generate the synthetic population. IPU's strength is in matching both household-level and person-level characteristics of interest. The algorithm iteratively adjusts and reallocates weights among a certain type of households until household- and person-level attributes are both matched with the marginal distributions of the true population.

Considering that we possess no household-level marginal data, we are unable to match any household-level attribute, and thus we only synthesize the person-level population. Using the sample data discussed in the previous section and marginal data entailing the number of employees in each department by gender, age, race, income and employment type, the sample of 327 employees is inflated to the full population of 2449 employees. The synthetic population procedure assigns the following attributes to each agent: socioeconomic attributes (gender, marital status, age, income, race, disability, and employment type); vehicle purchase information (frequency of car purchase in household and household WTP for adding automation and connectivity); travel behavior (flexibility of work schedule); social behavior (number of social ties at workplace, frequency of communication); and perceived barriers and incentives (13 items each rated on the seven-point scale).

5.2 Synthetic Network

Using response data to develop social ties among individuals requires a very extensive survey which is impossible to collect for a real-world problem. We therefore resort to generating a synthetic social network using socioeconomic attributes of the agents. The central concept in doing so is the *homophily* principle which indicates that the possibility that a pair of agents establish a connection is a function of geographical proximity and socio-demographic similarity (McPherson et al., 2001). Let I the set of agents, supplied from population synthesis. We define an 8-dimentional coordinate system by age, gender, race, employment type, income level, disability status, teleworking habit, and college/division.[4] Each agent is then placed in the 8-dimentional space, and the distance between each two agents i and j is calculated as $D_{ij} = \sqrt{\sum_{m\in S} \sigma_m \left(\frac{A_{m_i}-A_{m_j}}{\max A_m}\right)^2}$, 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 ($\forall k = i, j$), 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. In this study we set the weights for department and employment type (σ_{Emp} and σ_{Dep}) equal to 2 and other weights equal to 1. (Intuitively, in an academic environment, being in the same department and having the same employment type (faculty and non-faculty) seem to play more important roles in formation of social network.) Our primary analysis show that the values of the weights considered for each attribute can substantially impact network structure, and thus further research in this area is called for. Effectiveness of the social tie between agents i and j is defined by $w_{ij} = \frac{D_{ij}-\min_j D_{ij}}{\max_j D_{ij}-\min_j D_{ij}}$. The latter expression gives a weight of 1 to the tie with the closest agent to the given agent i and 0 to the one with the farthest.

We introduce a two-stage selection algorithm to choose the ties with the highest probability subject to the number of ties that each agent has. In Stage 1, the selection algorithm first calculates the distance between each two agents. Assume that each individual i has N_i social ties. If an agent j is among N_i closest agents to agent i *and* agent i is among N_j closest agents to agent j, the algorithm establishes a tie between agents i and j. Note that the order of selecting the agent indexed i can impact the structure of social network; thus, we randomly pick the agent indexed i. In Stage 2, the algorithm randomly selects an agent i and connects it to the closest agent which still have capacity for tie addition. It continues this process until N_i links established for agent i. Algorithm 2 below presents the steps of the selection process in detail. The social network established among UofM employees is shown in Figure 3.

[4] In reality, income and age are continuous while other variables are categorical. In our survey, however, we were unable to ask the exact amount of respondents' age and income because of privacy issues. Considering that our age intervals are relatively short, we assign a random age to each agent. An individual's age is drawn from the uniform distribution between the starting and ending points of the interval to which the individual belongs. For income, however, we stick to the categorical representation as our income intervals are not short, but are reasonable at the same time.

Algorithm 2: The selection algorithm that develops social network among individuals

Stage 1

Step 0 (initialization): Set $n_i = N_i, \forall i \in I$. Also set $I' = I$

Step 1: Calculate $D_{ij}, \forall i, j \in I | j \neq i$.

Step 2: For each agent $i \in I$, sort agents $j \in I | j \neq i$ such that D_{ij} values are in ascending order. Let SA_i denote the set of sorted agents. Clearly, the dimension of SI_i is $|I| - 1$ and the first element in that list (i.e., $SI_i(1)$) is the closest agent to *i* and the last one (i.e., $SA_i(|I| - 1)$) is the farthest.

Step 3: Randomly select an agent *i* from I'. If $n_i > 0$, store the first n_i elements of SI_i into SI'_i.

Step 4: For each element of SI'_i, i.e., $SI'_i(j)$, if *i* is in SI'_j, establish a tie between agents *i* and $SI'_i(j)$. Store the established tie in the list T. Set $n_i = n_i - 1$ and $n_{SI'_i(j)} = n_{SI'_i(j)} - 1$.

Step 5: Remove agent *i* from I'. Go to Step 3 and continue until I' becomes empty.

Stage 2

Step 0 (initialization): Set $I' = I$

Step 1: Randomly select an agent i from I'. If $n_i > 0$, go to the next step, otherwise, remove agent *i* from I' and randomly select another agent *i* from I', conditional on non-empty I'.

Step 2: For j equal to 1 to $|I| - 1$:

if $n_i > 0$ *and* $n_{SI_i(j)} > 0$ *and* there is no tie between agents *i* and $SI_i(j)$, establish a tie between agents *i* and $SI_i(j)$. Store the established tie in the list T. Set $n_i = n_i - 1$ and $n_{SI_i(j)} = n_{SI_i(j)} - 1$

Step 2: Remove the agent *i* from I'. Go to Step 2 and continue until I' becomes empty.

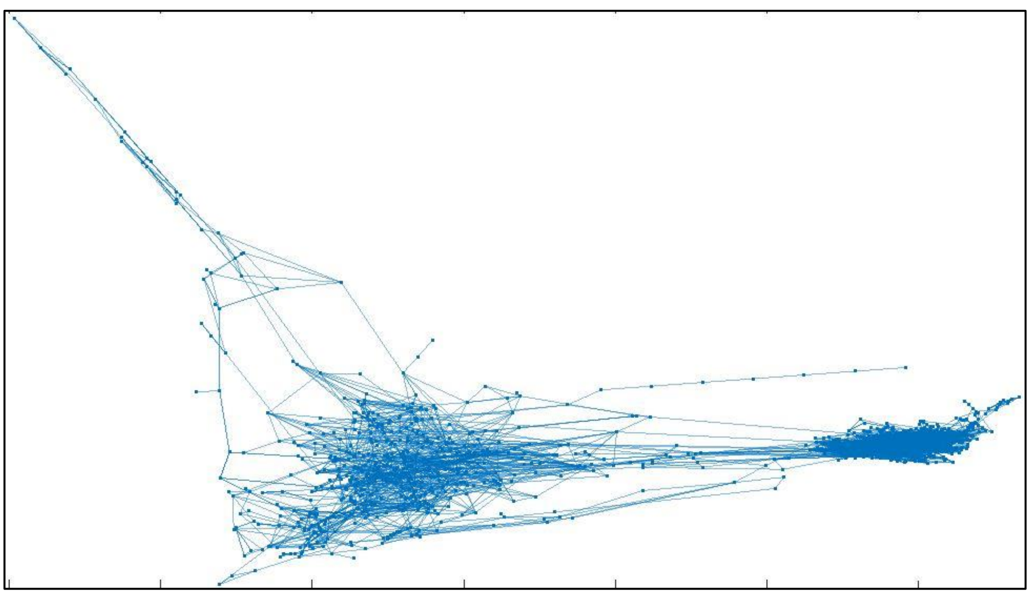

Figure 3: The social network established among UofM employees (isolated nodes are not shown)

6. Numerical Analysis

This section presents our numerical experiments of on CAV adoption of CAVs by UofM employees. We first describe modeling parameters and then present and discuss the results. The agent-based model is implemented in MATLAB 2017a and executed on a desktop computer with Windows 10 OS, Intel Core i5 3.1 GHz processor, and 8 GB memory. Running time for each simulation replication is about 20 seconds.

6.1 Parameter selection

The first step to numerical analysis is to determine appropriate values for the parameters involved in the model. We simulate CAV adoption over a 25-yer horizon, starting from 2025, discretized into two-week periods following Shafiei et al. (2015). We consider a pre-introduction marketing campaign of 6 months and vehicle purchase warm-up period of 7 years. Vehicles' lifetime is assumed to follow a normal distribution with a mean of 15.9 years and a standard deviation of 4.2 years (Mueller et al., 2007). The left tail of the distribution is truncated at 0 and the right tail at 30 years, which seems to be a reasonable maximum vehicle lifetime for the current vehicles in the market. We follow Bansal and Kockelman (2017) and assume that the additional cost of full automation is $40,000 at the base year, i.e., introduction year, and decreases at a specified annual rate. We set $\theta_2 = 0.05$ following Amini et al. (2012), and also assume that at each time point, a satisfied adopter may become dissatisfied with a probability $\theta_1 = 0.0001$. ρ is set equal to 1 which means that the effectiveness of the second round of exposure to media advertisement is half of the first round, and that of the third round is half of the second round and so on. Reasonably assuming that intercommunication effect dissipates at a lower rate, we consider $\alpha = 0.5$. Negative WOM is assume to be 4 times more effective as positive WOM.

Recall from Section 5 that a potential buyer calculates the weighted sum of various elements of its perception and compares it to the cutoff perception PI_C. To obtain reasonable values for $\varphi_l, \forall l \in L$, we conducted a brief survey in which 17 respondents of the main survey were contacted through email and requested to express a weight between 0 and 10 for each element. For each element $l \in L$, φ_l is set equal to the average of the weights stated by respondents. With the weights in place, the lower and upper bounds for the overall perception index are −419.9 and 102.2, which respectively correspond to the most pessimistic and optimistic perceptions about CAVs. We assume $PI_C \sim U(-54.4, -2.2)$. Note that -54.4 and -2.2 respectively correspond to 70% and 80% of perception span $(\text{i.e.}, 102.2 - (-419.9))$. This means that one is convinced to purchase a CAV when at least some 70% to 80% of the resistances he/she realizes is eliminated.

For each experiment, 10 repetitions are executed. Then the mean CAV market share is calculated and 95% confidence interval is established. In what follows, we scrutinize the impacts on adoption trend of other modeling parameters.

6.2 Modeling Results

Let us begin with the impact on vehicle fleet mixture of the annual rate of CAV price reduction. We conduct four experiments in which the reduction rate increases from 5% to 20% with an increment of 5%. In this analysis we assume that the impact of intercommunication on WTP follows $U(0,0.5)$. We further assume $\beta_{ij}^{l} \sim (0.5,1.0)$ and $\tau_{i,l} \sim (0.3,0.4), \forall l \in L$. Mean CAV market share and lower and upper bounds for the 95% confidence interval in the four scenarios are illustrated in Figure 4. The width of the confidence interval is at most 1.86% indicating that the simulation results are robust. CAV price reduction rate has significant impact not only on the ultimate amount of CAV market share in 2050 but also on the shape of adoption curve. With 5% rate, only some 15% of UofM employees will adopt by 2050. This share will reach about 90% if CAV price is reduced at 20%, annually. The impact of CAV price reduction is more evident in long term – more specifically after 2030.

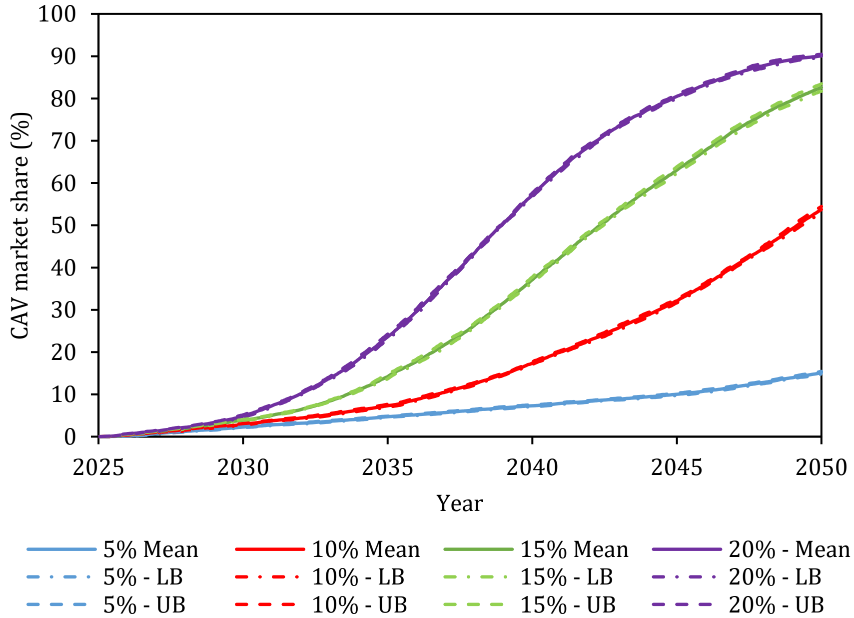

Figure 4: Mean CAV market share and 95% confidence interval (CI) bounds as a function of annual rate of CAV price reduction (LB: CI lower bound; UB: CI upper bound)

Next we study the possible impact of pre-introduction marketing. We scrutinize five scenarios, in the first of which no pre-introduction advertisement is considered. In the second to fifth experiments, the impact of marketing on each element of an agent's perception, i.e., $\tau_{i,l}$, follows $U(0,0.1)$, $U(0.1,0.2)$, $U(0.2,0.3)$, and $U(0.3,0.4)$, respectively. Post-introduction marketing impact is assumed to follow $U(0.3,0.4)$ and the learning factor, β_{ij}^{l}, be $U(0.5,1)$. Also, CAV price decreases at 10% rate, annually. The simulation results, shown in Figure 5, indicate that the impact of pre-introduction marketing on CAV market share is almost non-existent. This can be explained intuitively. A very small portion of the population is willing to pay for the very high introductory price of adding automation and connectivity. As a result, no matter how much pre-introduction marketing can address barriers, the group considering CAV adoption right after introduction remains the same. WTP of other users also remains almost intact considering that no significant intercommunication effect is added. Therefore, a pre-introduction marketing campaign of six month may not have any significant effects on CAV market share as long as CAVs are introduced to the market with high initial prices. This can have important implications for car manufacturers and marketing agencies.

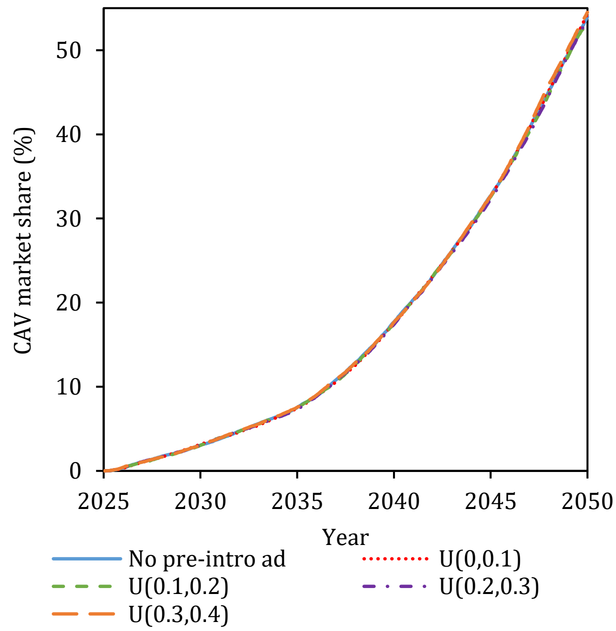

Figure 5: CAV market share as a function of pre-introduction marketing effect

DOI literature suggests that while advertisement initiates diffusion of an innovation, its impact is limited. Our next experiment examines this hypothesis about CAVs. Five scenarios are considered in which $\tau_{i,l}$ is zero (i.e., no marketing is undertaken) or follows $U(0{,}0.1)$, $U(0.1{,}0.2)$, $U(0.2{,}0.3)$, and $U(0.3{,}0.4)$. Here we assume CAV annual price reduction rate is 10%, $\beta_{ij}^{l} \sim U(0.5{,}1)$, and $\gamma_{ij} \sim U(0{,}0.5)$. The simulation results are shown in Figure 6. CAV market share will not be more than 4% if no advertisement is undertaken. Innovators, i.e., those that are more risk seeking and willing to obtain new technologies before others, form a tiny portion of population – typically less than 2.5%. WOM that is spread by such little portion can increase CAV market share by a limited extent. When $\tau_{i,l} \sim U(0{,}0.1)$, advertisement gradually changes the perceptions of more people. Starting from 2035, WOM propels the diffusion. By setting $\tau_{i,l}$ to $U(0.1{,}0.2)$ CAV market share surges but the share with $U(0.2{,}0.3)$ and $U(0.3{,}0.4)$ is almost the same as the share with $U(0.1{,}0.2)$ indicating that the impact on innovation diffusion of marketing is capped.

One important aspect of WOM is the impact on willingness-to-pay. We investigate this impact in Figure 7, where WOM does not change in the first experiment and γ_{ij} is $U(0{,}0.2)$, $U(0.2{,}0.4)$, $U(0.4{,}0.6)$, and $U(0.6{,}0.8)$ in the second to fourth experiments. Here our assumption is that the price reduction rate is 10%, $\beta_{ij}^{l} \sim U(0.5{,}1)$, and $\tau_{i,l} \sim U(0.3{,}0.4)$. Two points worth highlighting. First, CAV market share significantly grows with increase of the effect of intercommunication on WTP. Second, changing γ_{ij} has no significant effect on CAV market share in the early stages of adoption. The reason is that even with high change to WTP, a large number of individuals still envision CAVs as something incompatible with their existing practices and continue to defer adoption.

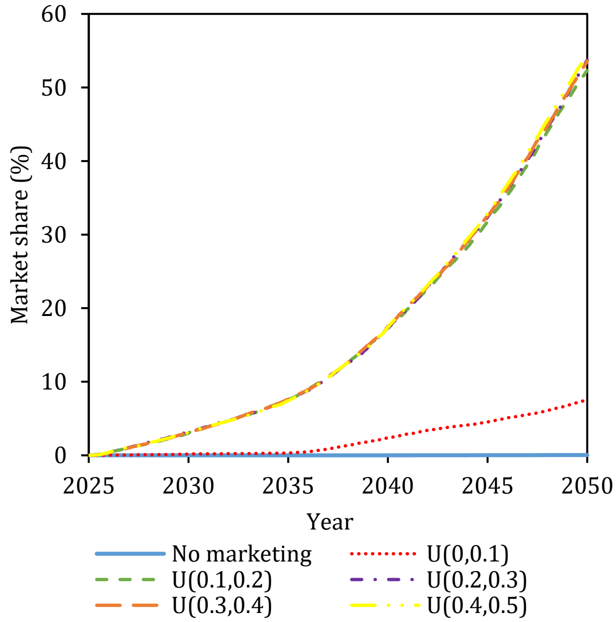

Figure 6: CAV market share as a function of marketing effect

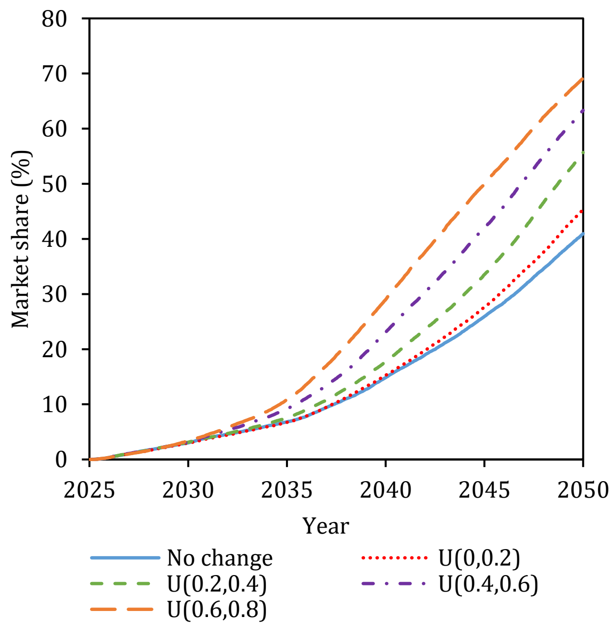

Figure 7: CAV market share as a function change to WTP due to intercommunication

Let us also look at the percentage of dissatisfied adopters and negative WOM spreaders (Figure 8). In this experiment CAV prices reduce at the rate of 10%. Also, it is assumed $\beta_{ij}^{l}\sim U(0.5,1)$, $\gamma_{ij}\sim U(0,0.5)$, and $\tau_{i,l}\sim U(0.3,0.4)$. Focusing on the left-hand-side panel, the percentage of dissatisfied CAV users is defined as the number of active dissatisfied adopters over the number of all adopters. This percentage and the corresponding confidence interval stabilize as time goes by. In 2050, the percentage of dissatisfied adopters is 3.6%, with a margin of error of 0.3%. A dissatisfied adopter continues to spread negative WOM even after switching back to conventional cars; thus, the percentage of negative WOM spreaders monotonically increases as illustrated in the right-hand-side panel of Figure 8. Here, the width of confidence interval also increases with time.

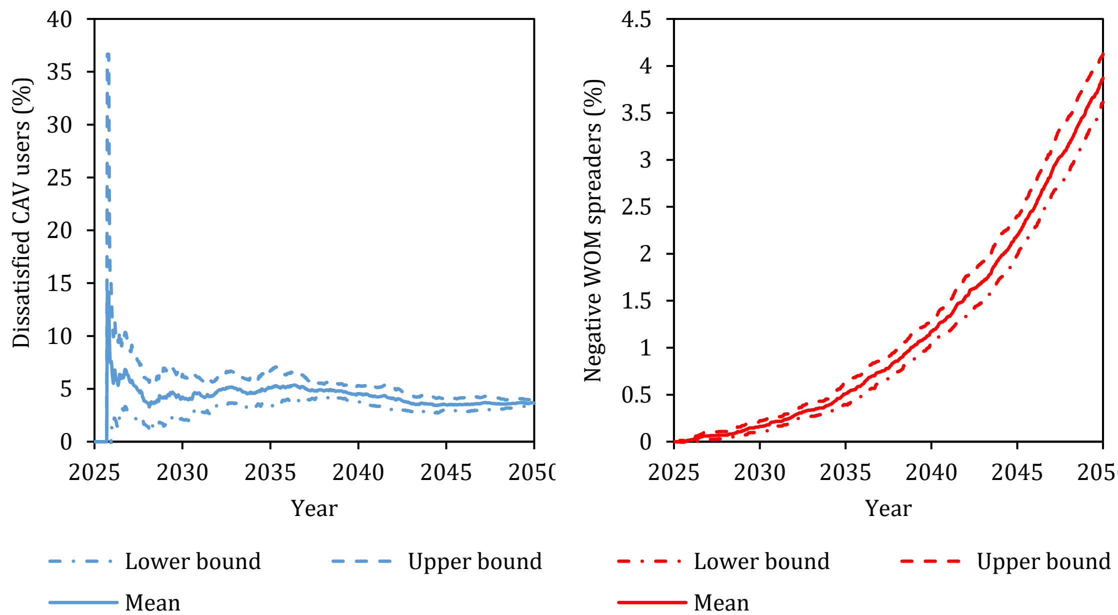

Figure 8: Percentage of dissatisfied adopters and negative WOM spreaders and corresponding confidence interval bounds

So far, we have assumed that $\theta = 0.05$. In Figure 9, we investigate how the value of θ impacts adoption trend. To this end, we let θ increases from 0 to 0.2 with 0.05 increments. For each experiment, we consider four scenarios of CAV price reduction. Other parameters are set as follows: $\beta_{ij}^{l} \sim U(0.5,1)$, $\gamma_{ij} \sim U(0,0.5)$, and $\tau_{i,l} \sim U(0.3,0.4)$. Three trends can be identified. First, an increase in θ lowers CAV market share because it elevates the number dissatisfied adopter. (Recall that a dissatisfied adopter switches to conventional cars in his/her next round of purchase.) As is observed in the lower-right panel, CAV market share approaches 100% only when the possibility of dissatisfaction is zero. Here, a 0.01 increase in θ lower CAV market share in 2050 by more than 1%. Second, the impact of θ on adoption trend is more pronounced for greater rates of price reduction. Third, the effect of θ value is more evident as time passes.

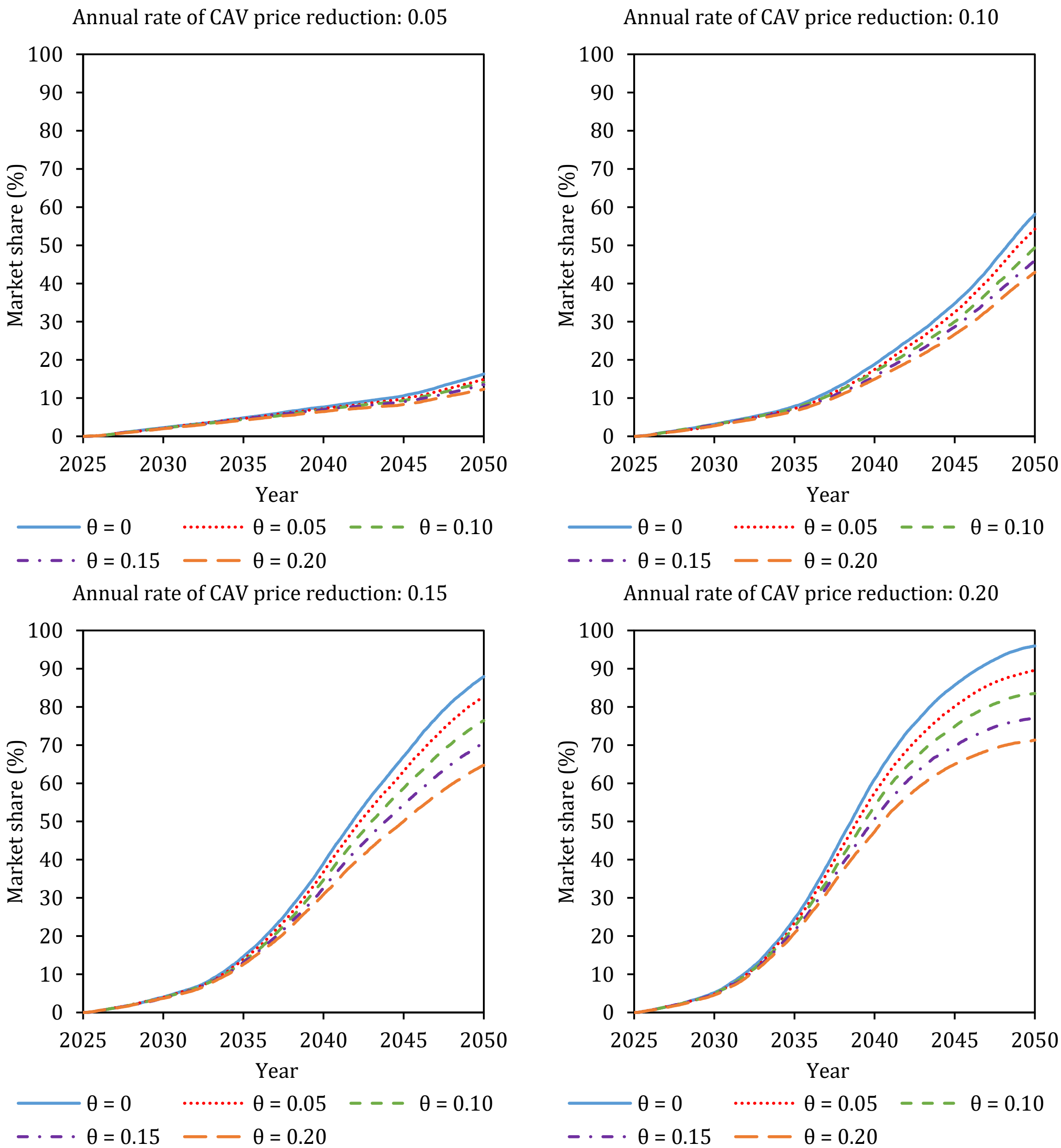

Figure 9: CAV market share as a function of θ, the probability of becoming a dissatisfied adopter, for four annual rates of CAV price reduction

7. Conclusion

Connected autonomous vehicles will hit the roads in the near future, faster than initial speculations. Over the past decade car manufacturers have substantially invested to make this technology viable and affordable, and academic community have made significant contribution to advance our knowledge about safety, travel behavior, and congestion effects of CAVs. Yet, the question that how people will adopt this new technology in long-term is not well researched. The studies addressing CAV adoption use expert knowledge, sales estimates, and discrete choice modeling to explain how transportation fleet will be transformed in the next decades. Discrete choice models assume that an individual's expectations are the same as the market outcome, and therefore stated preferences will remain valid.

This, however, may not be true about CAVs because individuals have no previous experience on which they can base their expectations. Empirical studies suggest that individuals heavily rely on the information they receive from their peers when assessing adoption of a radical innovation such as connected autonomous vehicles.

This study is the first of its kind to couple the theory of Diffusion of Innovation and agent-based modeling to forecast long term adoption of CAVs. The concept of resistance is used to explain why individuals typically tend to defer adoption of an innovation. We assume that there exists a social network among individuals through which they communicate based on certain frequencies. In addition, individuals can be subject to media advertisement (marketing) again based on certain frequencies. An individual’s perceptions are dynamic and change over time when the individual is exposed to media advertisement or communication with satisfied and dissatisfied adopters. The individual’s willingness-to-pay for automation is also dynamic and changes as result of intercommunication. This means that communication with a satisfied adopter can not only convinces a potential adopter that the barriers which he/she perceives are not real (or perhaps not as important as he/she thinks) but also it is worth spending more money on CAVs. Media advertisement has similar impacts on individuals’ perceptions but to a lesser extent.

We show applicability of the proposed approach using a survey of 327 employees of the University of Memphis. The survey aims to (i) understand how individuals rely on their social network when assessing the purchase of CAVs; (ii) investigate how individuals think about various barriers and incentives associated with adoption of CAVs; and (iii) develop a seed for population synthesis. Multivariate normal is performed to fill-in missing values of survey data. Then the full population of UofM employees is synthesized using Iterative Proportional Updating procedure. The synthetic network among individuals is generated based on the concept of *homophily* which states that the individuals with geographical proximity and socio-demographic similarity are more likely to form a social tie. We then simulate the market share of CAVs over a 25-year time period, starting from 2025.

Our numerical analysis indicates that the automobile fleet will be nearly homogenous in about 2050 only if CAV prices decrease at significant rates (e.g., 15% or 20% annually). With a 5% annual rate of price reduction, CAVs will only be about 15% of all vehicles. We find that a 6-month pre-introduction marketing campaign may have no significant impact on adoption trend. Our results further confirm that marketing impact does initiate CAV diffusion but the effect of marketing is capped. CAV market share is also found to significantly alter as a result of changes in WTP caused by intercommunication. CAV market share will be close to 100% only if all adopters are satisfied with their purchases; therefore, the probability that an individual becomes a satisfied adopter plays an important role in the trend of adoption. The effect of the latter probability is more pronounced as time goes by and is also more prominent when CAV price reduces at greater rates.

The current work can be extended in a few directions. First behavioral research is suggested to understand other barriers and incentives that are possibly missed in the current research. Due to data limitations, this study does not account for adoption of used cars, multiple technology generations, car types (SUV, sedan, van, etc.) and classes (luxury, economy, sport, etc.). By collecting richer datasets, these simplifications can be addressed and more detailed modeling components (e.g., more advanced purchase models) can be developed. Our analysis is based on only work social networks of a population with certain employment types. With more diverse data, our modeling results can be validated and more solid conclusions can be made.

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