Modeling consumers' likelihood to adopt autonomous vehicles based on their peer network

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Abstract

Adoption of connected and autonomous vehicles (CAVs) is viewed as one of the vital factors by public and private agencies as benefits are slowly getting quantified with further advancement in technology. From a wide variety of CAV perception and demand estimation studies, the literature lacks the impact of adoption based on an individual's social network and values. In this paper, we utilize an integrated choice and latent variable model to capture individuals' likelihood to adopt level 4 CAVs based on their social values in their peer network using an institutional survey dataset. The model results suggest that households with high income and frequent car buyers are more likely to adopt CAVs. CAV adoption will have a positive influence on an individual's social values among his peers. The proposed framework can be used to provide useful insights for policymakers to quantify consumers' preferences about CAV adoption based on their social values.

Keywords: integrated choice and latent variable model, latent attitudes, exploratory factor analysis, ordinal logit, structural equation modeling.

1. Introduction

Connected and autonomous vehicles (CAVs) will be an intrinsic part of the daily travel modes, in terms of personal, public or shared mobility, shortly because of their potential of technology-assisted driving and hence minimizing errors caused by human drivers (Fagnant and Kockelman, 2015; Gurney, 2013). Society of Automotive Engineers (SAE) and National Highway Traffic Safety Administration (NHTSA) define five levels (0-5) of driving automation, where the lowest being no automation and highest being full automation (Kyriakidis et al., 2015). In addition to safety, CAVs will provide additional benefits in terms of ability to multitask during travel, flexibility in travel (relocating the house to farther and more convenient location), reduced parking and running costs, travel time savings due to the reduction in congestion and accessibility to elder and non-license holder individuals. However, such benefits will also come at the cost of numerous anticipated barriers like accident liabilities, data safety concerns, the addition of new infrastructure and increased emissions because of increase in vehicle miles traveled (Becker and Axhausen, 2017; Fagnant and Kockelman, 2015; Gkartzonikas et al., 2019; Gurney, 2013; Milakis et al., 2017).

In the US, after Nevada in 2011, 21 other states have already passed legislation for autonomous vehicle operation on public roads (NCSL, 2018). Almost every global automaker company is committed to investing in research, development, and manufacturing of CAVs with plans to have its market penetration from 2020 (Walker, 2018). Google's driverless ride-hailing company's (Waymo) driverless cars are already offering services in Arizona, Phoenix (Waymo, 2018). These trends and many others, vindicate the imminent dominance of CAVs in providing mobility in the next decade. However, such commitments from government legislation, automotive manufacturers, and technology-related companies will not be enough for CAV adoption until the CAVs meet the perceptions, demands, beliefs, and needs of end-users at a justified cost. Also, it will be more of a paradigm shift to adopt CAVs from the existing human-driven conventional vehicles in addition to their anticipated barriers and benefits of CAVs.

There are numerous studies available in the literature to document these perceptions and preferences of individuals towards the CAV adoption (Asgari and Jin, 2019; Bansal and Kockelman, 2017; Daziano et al., 2017; Haboucha et al., 2017; Howard and Dai, 2014; Lavieri et al., 2017; Leicht et al., 2018; Liu et al., 2019a; Nazari et al., 2018; Nordhoff et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Shin et al., 2015a; Simpson et al., 2019; Simpson and Mishra, 2020; Spurlock et al., 2019; Talebian and Mishra, 2018). In these studies, choice models in the form of binary logit (Cunningham et al., 2019), multinomial logit models (Bansal and Kockelman, 2017; Howard and Dai, 2014; Malokin et al., 2015), mixed logit models (Daziano et al., 2017; Haboucha et al., 2017; Krueger et al., 2016a), ordered logit models (Menon et al., 2015), latent class choice models (El Zarwi et al., 2017), the generalized heterogeneous data model (GHDM) (Lavieri et al., 2017) and hybrid choice model (Krueger et al., 2016b; Nazari et al., 2018) have been extensively used to study the individuals' preferences towards CAV adoption utilizing stated preference survey datasets.

Adoption behavior of users in the future is expected to be affected due to the exposure and experience of the CAV technologies through social media, household, or workplace interactions (Bansal and Kockelman, 2017). Adoption research from non-transportation related innovations suggests that social network plays a pivotal role in deciding whether to adopt (Cheung et al., 2014; Venkatesh et al., 2003; Wang et al., 2012). Also, the influence of social interaction on individuals' decisions to adopt an innovation depends on the individual's attitudes (Wang et al., 2008). To best of our knowledge, past efforts to study the likelihood to adopt a CAV, while considering social network and interaction, are limited (Leicht et al., 2018; Liu et al., 2019b; Nordhoff et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Spurlock et al., 2019), especially using discrete choice modeling (DCM). Traditional DCM techniques measure an individual's choice behavior based on alternative attributes and an individual's socioeconomic characteristics using tractable models. Also, it has been well established in the past literature that attitudes and perception play an intrinsic role in choice behavior (McFadden, 1986) but, DCM alone cannot capture the irrational behaviors, effect of perception and attitude on the decision process (Atasoy et al., 2013). Attitudes and perceptions being latent can be efficiently analyzed using integrated choice and latent variable (ICLV) or hybrid choice models. Such models are an extension of DCM to capture attitudes and perceptions while relying on structural equation modeling (SEM) to estimate latent variables (Ben-Akiva et al., 2002; Bouscasse, 2018). The ICLV modeling framework is being extensively used to capture the effect of attitudes in choice behavior, especially in travel mode choice (Bouscasse, 2018). In the upcoming subsections, we review the past related literature available on the adoption of CAVs.

1.1. Literature Review

This section includes the methodological framework and significant findings of previous studies related to capturing the intention or likelihood to own/adopt and the impact of social influence on the likelihood to adopt. Several studies are available in the literature to investigate user's likelihood to adopt a CAV or to install autonomous vehicle (AV) technology in the existing vehicles (Acheampong and Cugurullo, 2019; Asgari and Jin, 2019; Bansal and Kockelman, 2017; Berliner et al., 2019; Casley et al., 2013; Daziano et al., 2017; Haboucha et al., 2017; Howard and Dai, 2014; Jiang et al., 2019; Kaur and Rampersad, 2018; Kyriakidis et al., 2015; Lavieri et al., 2017; D. Lee et al., 2019; J. Lee et al., 2019; Liljamo et al., 2018; Liu et al., 2019b; Manfreda et al., 2019; Nair et al., 2018; Payre et al., 2014; Pettigrew et al., 2019; Schoettle and Sivak, 2014a, 2014b; Shabanpour et al., 2018, 2017; Shin et al., 2015b; Tussyadiah et al., 2017; Wang and Zhao, 2019), based on social influence (Leicht et al., 2018; Liu et al., 2019b; Nordhoff et al., 2018; Spurlock et al., 2019) while utilizing structural equation models (Asgari and Jin, 2019; Liu et al., 2019a; Payre et al., 2014) and hybrid choice models (Nazari et al., 2018). The major findings of all studies which captured the likelihood to adopt CAVs, along with their data, considered level of autonomy (level 3 to 5) and methods, are delineated in Table 1.

1.1.1. Social influence

Although research on the impact of an individuals' social network on their likelihood to adopt CAV is limited, some studies mentioned in Table 1 have considered this effect through social influence either directly (Leicht et al., 2018; Nordhoff et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018) or indirectly (Liu et al., 2019b; Spurlock et al., 2019).

Leicht et al. (2018) defined social influence based on three survey questions, i.e., people will adopt CAVs because others adopt them too; people will buy CAV as it will look them good in front of their friends; all cars will be CAVs as people tend to imitate the buying behavior of their family and friends. Nordhoff et al. (2018) defined social influence based on two Likert scale survey questions: whether people important to respondents will like it when they use a CAV and whether the respondents would like their friends or family to adopt CAVs before they do. Panagiotopoulos and Dimitrakopoulos (2018) defined social influence based on two survey questions: people, whose opinions are valuable to the respondent, will adopt CAVs; Respondents would feel proud if people in their social network see them adopting a CAV.

Liu et al. (2019b) described social influence as the trust of an individual on an automaker manufacturer, government authorities, and technology-based companies. Spurlock et al. (2019) considered social interaction in the form of a characteristic of a transportation mode where whether an individual can choose to interact with other passengers other than family and close friends.

Table 1

Major findings from previous studies on individual's likelihood to adopt CAVs

Source	Data (level of autonomy: L3, L4, and L5)	Approach/Method	Major findings
United States of America			
Casley et al. (2013)	Survey: 467 American respondents (L4 and L5)	Survey data analysis	31% of respondents' decision to adopt CAV was influenced by cost, and 61% of respondents would wait at least three years to adopt a CAV.
Howard and Dai (2014)	Survey: 107 American respondents (L4 and L5)	Logit model	42% of respondents were more likely to adopt CAVs.
Bansal et al. (2016)	Survey: 347 American respondents (L4 and L5)	Ordered probit	Males with high household income, individuals who travel more, and individuals living in urban areas were inclined to adopt CAV as soon as they are available.
Daziano et al. (2017)	Survey: 1,260 American respondents (L4 and L5)	Mixed-mixed logit model	Individuals knowing existing automation technologies were inclined to adopt CAVs.
Bansal and Kockelman (2017)	Survey: 2,167 American respondents (L4 and L5)	Simulation-based multinomial logit model	Around 40% and 33% of respondents were willing to use CAVs for daily trips and their children's school trips, respectively.

Lavieri et al. (2017)	Survey: 1,832 American respondents (L4 and L5)	Generalized heterogeneous data model	Young and more educated individuals living in urban areas with a tech-savvy lifestyle would be among the early adopters of CAVs.
Shabanpour et al. (2017)	Survey: 1,253 American respondents (L3, L4, and L5)	Random parameter logit model	Individuals with accident history, high annual mileage, living far away from the workplace, innovators, and favorable policies in terms of dedicated lanes were related positively with the likelihood to adopt CAVs.
Tussyadiah et al. (2017)	Survey: 325 American respondents (L4 and L5)	Hierarchical regression analysis	Individuals were inclined to use CAV taxi as a tourist than as a resident.
Nair et al. (2018)	Survey: 1,365 American respondents (L4 and L5)	Rank ordered probit model	Males, multi-person households, and individuals driving alone to work were more inclined to own CAVs.
Nazari et al. (2018)	Survey: 2,726 American respondents (L4 and L5)	Hybrid choice model	Men, young adults, self-employed, primary drivers for the household vehicle, and green travel patterns were positively related to adopting a CAV.
Shabanpour et al. (2018)	Survey: 1,253 American respondents (L3, L4, and L5)	Multinomial logit model	People with disabilities, higher income, and high level of education would be among the early adopters of CAVs.
Asgari and Jin (2019)	Survey: 1,198 American respondents (L3, L4, and L5)	Structural equation model	Only 12% of respondents intended to ride in CAV in the next ten years, and tech-savvy respondents were more likely to adopt CAVs
Berliner et al. (2019)	Survey: 2,261 American respondents (L3, L,4 and L5)	Ordered logit model	Men, larger households, paying more for buying a new vehicle, increased knowledge about AV technology, and perceiving CAVs safer than

			conventional vehicles were associated with an increased likelihood of adopting a CAV.
Spurlock et al. (2019)	Survey: 1,045 American respondents (L3, L,4 and L5)	Linear probability model	Individuals willing to interact with other passengers while traveling (social interaction) were reluctant to show interest in adopting autonomous technology.
Countries from the rest of the world			
Payre et al. (2014)	Survey: 421 French respondents (L4 and L5)	Hierarchical regression analysis	At least 66% of respondents were inclined to use CAVs.
Shin et al. (2015)	Survey: 675 South Korean respondents (L3)	Multinomial probit	An individual's decision to adopt CAVs depends primarily on its price, followed by automation technology.
Kaur and Rampersad (2018)	Survey: 101 Australian respondents (L4 and L5)	Confirmatory factor analysis	The positive influence of reliability, performance expectancy, and trust on likelihood to adopt CAV.
Leicht et al. (2018)	Survey: 241 French respondents (L3, L4, and L5)	Technology acceptance model	Consumer innovativeness had a positive impact on social influence and intention to purchase CAVs.
Liljamo et al. (2018)	Survey: 2,036 Finnish respondents (L3, L4 and L5)	Cross-tabulation	Men, highly educated individuals, living in densely populated areas, and not owning a vehicle, had positive attitudes towards CAVs.
Panagiotopoulos and	Survey: 483 Greek respondents (L,3, L4 and L5)	Technology acceptance model	The social influence had positive impacts on behavioral intention to use CAVs.

Dimitrakopoulos (2018)			
Acheampong and Cugurullo (2019)	Survey: 507 Irish respondents (L4 and L5)	Confirmatory factor analysis	Almost 55% of respondents believed that CAVs would become a standalone mode of travel in the future.
Jiang et al. (2019)	Survey: 576 Japanese respondents (L3, L4 and L5)	Mixed logit model	At least 47% of respondents were willing to adopt level 3+ CAVs.
J. Lee et al. (2019)	Survey: 313 Korean respondents (L3, L4, and L5)	Structural equation model	Psychological ownership and self-efficacy attitude towards CAVs promote their adoption.
Liu et al. (2019b)	Survey: 441 Chinese respondents (L5)	Structural equation model	Direct and indirect effects of social trust on CAV acceptance: The indirect effect of social trust developed through risk and benefits described acceptance, whereas the direct effect described willingness to pay and behavioral intention.
Manfreda et al. (2019)	Survey: 382 Slovenian millennial respondents (L4 and L5)	Structural equation model	Perceived concerns and benefits towards CAVs were related negatively and positively, respectively, with their adoption.
Pettigrew et al. (2019)	Survey: 1,314 Australian respondents (L4 and L5)	Latent profile analysis	First movers were among the first buyers and most knowledgeable about CAVs, followed by likely adopters and AV ambivalent.

Wang and Zhao (2019)	Survey: 1,142 Singaporean respondents (L4 and L5)	Mixed logit model	Elderly, females, poor and unemployed are more susceptible to risk, hence less likely to adopt a CAV.
Multiple countries			
Schoettle and Sivak (2014a)	Survey: 1,533 respondents across the US, UK, and Australia (L3, L4 and L5)	Survey data analysis	At least 21%, 18%, and 14% of individuals in the US, UK, and Australia were very interested in adopting CAVs.
Schoettle and Sivak (2014b)	Survey: 1,722 respondents across China, India, and Japan (L3, L4 and L5)	Survey data analysis	At least 40%, 47%, and 9% of individuals in China, India, and Japan were very interested in adopting CAVs.
Kyriakidis et al. (2015)	Survey: 5,000 respondents across 109 countries (L3, L4 and L5)	Correlation analysis	69% of individuals believed that CAVs would reach 50% market share by 2050.
Haboucha et al. (2017)	Survey:721 American and Israeli respondents (L4 and L5)	Nested logit kernel model	44% of users were in favor of continuing with their regular cars, while 32% of users opted for personally owned CAVs, and remaining users were in favor of shared CAVs.
Nordhoff et al. (2018)	Survey: 7,775 respondents across 109 countries (L5)	Spearman correlation analysis	Social influence among individuals was regarded as a deciding factor for the acceptance of CAVs.
Lee et al. (2019)	Survey:721 American and Israeli respondents (L4 and L5)	Mixed logit and gradient boosting machine	Trip cost, purchase price, and Pro-AV attitude were the deciding factors for an individual to choose CAV.

1.2. Contribution

The summary of the literature suggests that studies are scarce in capturing the impact of individual's social network on their likelihood to adopt a CAV based on DCM framework as Leicht et al. (2018), Panagiotopoulos and Dimitrakopoulos (2018) and Nordhoff et al. (2018) utilized SEM, technology acceptance model, principal component analysis, respectively. Also, other previous studies (Liu et al., 2019b; Spurlock et al., 2019) considered the social influence in terms of social trust on various agencies and social interaction during the commute (whether an individual is willing to have a conversation with a fellow passenger) instead of the influence of individuals' social network. Therefore, the contributions of this study are threefold. *First*, to identify user's perception towards the adoption of CAVs based on an individuals' attitudes towards anticipated (i) Impact on social values after buying a CAV, (ii) Barriers associated with CAVs, (iii) Benefits associated with CAVs, (iv) Purchase characteristics (price, quality, and environment) associated with CAVs. *Second*, to test the hypothesis, "owning a CAV will increase an individual's social status just similar to buying a luxury car." *Third*, to capture users' likelihood to adopt a CAV based on their social network interaction. We utilized an ICLV modeling framework based on an institutional survey dataset to test the hypothesis and capture the likelihood to adopt CAVs. The survey dataset included perceptions and attitudes towards level 4 CAVs. As per NHTSA, a level 4 CAV has environmental detection and human equivalent driving capabilities under certain circumstances and requires the human driver to take over during an emergency.

The paper consists of five sections. Section 2 presents the description of the dataset used; Section 3 describes the methodology of the ICLV modeling framework; Section 4 presents the model results, and the discussions with previous studies; and finally, Section 5 concludes the paper with key findings, limitations and future scope of the study.

2. Data

The dataset utilized in this study is based on an institutional stated preference survey data sent to 2,449 full-time employees (faculties and staff) of The University of Memphis, Tennessee, in 2017 (Talebian and Mishra, 2018). The survey consisted of 41 questions subdivided into four different blocks with an approximate completion time of 10 minutes. In the first and second blocks, individuals were asked about their socioeconomic characteristics (both at the individual and household level) and vehicle ownership and purchasing behaviors. In the third block, respondents were asked their social influence characteristics, including questions about their social network in terms of the social ties established in the workplace and frequency of communication with them. Finally, the fourth block included questions about the benefits and barriers associated with CAVs.

The online survey was hosted in Qualtrics and distributed through institutional emails, and twenty-five Amazon gift cards worth $25 were offered as an incentive to randomly chosen respondents. In the survey, participants were given a brief description of CAVs (level 4) just before introducing the fourth block: *"A self-driving car is a vehicle that is capable of sensing its environment and navigating without human input. No driver attention is required for safety; i.e., the driver may safely go to sleep or leave the driver's seat. Self-driving is supported under certain circumstances and areas. Outside of these areas or circumstances, the car will be able to safely abort the trip, i.e., park the car, if the driver does not retake control".*

During the two-week survey distribution, 327 responses were recorded with a response rate of 13.3%. Since covering each individual through a survey tends to be more costly and difficult, as an alternative, it is possible to expand the collected aggregated data to generate an artificial or synthetic population representing the true population. Therefore, the collected responses were further expanded to an entire institutional population of 2,449 using the synthetic reconstruction

(SR) approach (Auld and Mohammadian, 2010; Guo and Bhat, 2007; Talebian and Mishra, 2018). The SR approach is based on an Iterative Proportional Updating (IPU) algorithm, which is capable of matching both person-level and household-level characteristics of interest. Since the survey did not include any household-level analysis, only person-level synthesis was employed.

2.1 Descriptive statistics

Descriptive statistics of categorical and continuous attributes or variables with their modeling notation is presented in Table 2 and Table 3, respectively. For categorical variables, original survey responses for each question had different levels than in Table 2 because for modeling purposes, we reclassified these levels to keep either equal percentage of responses in each level or at least 25% percentage of responses in each level. This reclassification applies mainly to variables such as age, personal income, household income, and willingness to pay towards a regular car. The dataset includes 53% male participants, 35% aged above 54, 58% white, 26% with income less than $35,000, 4% physically challenged, 18% willing to pay $10,000 more than a regular car to buy a CAV, almost 90% owned a smartphone and on an average, five social connections established at the workplace.

Table 2

Descriptive statistics of the categorical attributes (N = 2,449)

Attribute (variable name)	**Percentage**	**Attribute (variable name)**	**Percentage**
Gender (Gender)		Disability limiting driving ability (Disability)	
Male	53%	Yes	4%
Female	47%	No	96%
Age (Age)		Approximate annual household income (HHIncome)	
Less than 40	28%	less than $65,000	36%
40 to 54	38%	$65,000-$110,000	38%
more than 54	35%	more than $110,000	26%
Race (Race)		Frequency of purchasing a car (CarPurchFreq)	
White	58%	Frequently (once every 1 to 5 years)	35%
Black or African American	33%	Moderate (once every 10 years)	44%
Others	9%	Infrequent (once every 15 to 20years)	21%
Employee category (Emptype)		Any plans to buy or sell a car in the next three years (CarNext3)	
Staff	67%	Yes	50%
Faculty	33%	No	50%
Approximate annual income (Income)		Willingness to pay towards buying a regular car (WTP_RegularCar)	
less than $35,000	26%	less than $15,000	30%
$35,000-$65,000	44%	$15,000-$30,000	48%
more than $65,000	30%	more than $30,000	21%
Frequency of working from home (TeleWorkfreq)		Flexible work schedule (ScheduleFlex)	
Frequent (daily to once a week)	30%	Yes	56%
Sometimes (once in a month or year)	28%	No	44%

Never	42%		
Willingness to pay more towards buying a CAV than a regular car (CAV_Adopt)		Annual willingness to pay towards maintaining a CAV than a regular car (WTP_AV_AnnMaint)	
less than $2,500 (Less)	38%	Nothing or $0	32%
$2,500-$10,000 (Moderate)	44%	$0-$300	34%
more than $10,000 (More)	18%	more than $300	33%
Frequency of communication with social ties developed at work (CommFreq)		Listens to Radio (Radio)	
Frequent (daily to 2-3 times a week)	82%	Yes	97%
Sometimes (2-3 times a month)	11%	No	3%
Infrequent (2-3 times a year)	8%		
Own a Smartphone (Smartphone)		Watches TV (TV)	
Yes	90%	Yes	97%
No	10%	No	3%

To the best of our knowledge, we did not find any previous study targeting institutional population; however, we compared our sample (N=2,449) with Nazari et al. (2018) (N= 2,726), where authors used Puget Sound regional travel survey program dataset to study the public interest in adopting owned and shared autonomous vehicles and is delineated in Table 4. The proportion of males and females in our sample is almost equal to Nazari et al. (2018). Also, the age statistics are similar to Nazari et al. (2018), with a difference of 7% and 6% in respondents aged between 18 to 35 and more than 35, respectively. Both the samples have a similar household income of less than $50,000 (2% difference) and a difference of 4% and 5% in household income $100,000 to $150,000 and more than $150,000, respectively. However, the number of household members and vehicle ownership was 36% more and 40% less in our sample as compared to the survey sample of Nazari et al. (2018).

Table 3

Descriptive statistics of the continuous attributes (N = 2,449)

Attribute (variable name)	Percentage	Attribute (variable name)	Percentage
Number of household members (HHSize)		Number of owned cars (household) (HHCars)	
1	23%	0	29%
2	34%	1	46%
3	20%	2	19%
4	14%	3	6%
5+	8%		
New cars purchased over the last ten years (HHCarsHist10)		Used cars purchased over the last ten years (HHCarsHistUsed10)	
0	8%	0	34%
1	31%	1	24%
2	33%	2	21%
3	17%	3	13%
4+	12%	4+	7%
Number of close social ties established at work (SocTies)			
Mean	4.79		
Standard deviation	4.96		
Median	4		
Minimum	0		
Maximum	25		

A unique element of the survey was to capture respondent's perception towards the importance of medium of reliable information, input from the social network, impact on personal and social status, barriers, benefits, and attractiveness associated with CAVs, when purchasing a self-driving car, through 23 questions in survey with 7-point Likert response scale (one being very unimportant and seven being very important). Table 5 summarizes the descriptive statistics of indicator variables (Ind01- Ind23) Likert with their notation and description, which we further used in model estimation.

Table 5 also includes the percentage of responses for all Likert scale levels of indicator variables. Individuals were not concerned about CAVs being less safe than a regular car. Not surprisingly, individuals were highly concerned about almost all the barriers in terms of CAV breakdown due to system failure, virus attack, and poor internet connection. Individuals were least concerned about losing friends who will not buy CAVs and improvement in social status or personal image after buying a CAV. As expected, respondents were highly concerned about the benefits of CAVs in terms of providing mobility for disabled and generating less pollution as compared to regular cars. Individuals were moderately concerned about the input from their social network when purchasing a CAV. Individuals rated personal research and social ties who already purchased a CAV as the most important factor in deciding on purchasing a CAV. Respondents were highly concerned about the price and quality of CAVs in finalizing their purchasing decision.

2.2 Dependent variable (ordered): Likelihood to adopt a CAV

To capture an individual's intention to buy a CAV, we use the question, asking respondent about the reasonable amount they would pay to own/adopt a personal CAV, as the dependent variable, i.e., "*How much MORE would you be willing to pay for a self-driving car than you would* *be willing to pay for a standard car (the one you must operate)?*" We then transformed the numerical responses into ordinal with three levels based on the significant percentages in each level and keeping the incipient stage of CAVs and their anticipated initial price: *less likely (<=$2,500), equally likely ($2,500-$10,000), and more likely (>=$10,000)*.

Table 4

Descriptive statistics: comparison with Nazari et al. (2018)

Categorical attributes	**Share (%)**	
	This study (N = 2,449)	**Nazari et al. (2018) (N = 2,726)**
Gender		
Male	53%	54%
Female	47%	46%
Age		
18 to 35	17%	23%
more than 35	83%	77%
Household income		
less than $50,000	25%	27%
$50,000-$75,000	24%	15%
$75,000-$100,000	25%	15%
$100,000-$150,00	14%	19%
more than $150,000	11%	15%

Continuous attributes	**Mean (SD)**	
	This study (N = 2,449)	**Nazari et al. (2018) (N = 2,726)**
Number of household members	2.52 (1.23)	1.85(0.66)
Number of owned cars (household)	1.01(0.84)	1.67(1.06)

We used an ordinal dependent variable to complement the results of Cunningham et al. (2019) which included a binary dependent variable representing WTP more against not willing to pay anything and ordinal dependent variables fall under common practice in previous studies (Joewono, 2009; Kim and Vandebona, 1999; Lera-López et al., 2014; Wolinetz et al., 2001). Approximately 18% and 38% of respondents were less and more likely to adopt a CAV, which are marginally close to Cunningham et al. (2019) (23% and 43%).

Since the dependent variable is based on another question in the dataset, represented by variable "Willingness to pay towards buying a regular car (WTP_RegularCar)," to check the endogeneity between the variables, we performed Durbin-Wu-Hausman (DWH) test (LaFrance, 1993). We used household income (HHIncome) as an instrumental variable based on relevancy and strength test; HHincome was the best representator of WTP_RegularCar as per significant F-test results (F-value = 265.33 at p<0). DWH test results indicated that the WTP_RegularCar is not endogenous to the model as F-test results were not significant (F-value = 0.89 at p=0.35).

We considered all explanatory variables for the modeling, including socioeconomic variables, alternative attributes - associated with vehicle purchasing behavior - and social influence variables. In order to avoid multicollinearity, we performed a correlation analysis for all the variables (Spearman for continuous and Cramer's V for categorical), and all the included variables had very little or moderate correlation (Hinkle et al., 2003). We kept both annual income (personal) and annual household income variables in the dataset to capture the likelihood of adopting a CAV at the person and household level as there was no correlation between these variables. We then divided the dataset as **70:30** for model training and cross-validation, respectively.

Table 5

Descriptive statistics of the Likert attributes (N = 2,449)

Variable name	Likert scale variables	Likert Scale levels: Very Unimportant (1) to Very Important (7)							Mean	SD.
		1	2	3	4	5	6	7		
Ind01: PersonalImage	Importance to personal image while purchasing a car	17%	27%	12%	18%	19%	4%	2%	3.16	1.60
Ind02: WorkSocialNetImp	Importance of input from work social network when purchasing a self-driving car	6%	8%	10%	16%	29%	24%	6%	4.51	1.58
Ind03: NonWorkSocialNetImp	Importance of input from non-work social network when purchasing a self-driving car	6%	7%	7%	15%	31%	25%	8%	4.65	1.60
Ind04: StatusImprove	Owning a self-driving car will improve individual's status among his peers	37%	33%	9%	17%	2%	1%	2%	2.22	1.35
Ind05: LoseTies	Owning a self-driving car may result in losing friends who won't purchase self-driving car	41%	32%	4%	17%	1%	5%	1%	2.26	1.49
Ind06: PoorInternet	Self-driving feature may fail under poor internet connection	3%	1%	2%	10%	9%	25%	52%	6.02	1.39
Ind07: TakeOver	Driver should take over when CAV fails under poor internet connection	1%	0%	3%	5%	7%	27%	56%	6.22	1.19
Ind08: VirusAttack	Unexpected operations of self-driving car due to virus attack	1%	0%	0%	3%	1%	23%	71%	6.60	0.81
Ind09: SystemFailure	Unexpected operations of self-driving car due to operating system failure	1%	0%	0%	3%	5%	23%	69%	6.56	0.81
Ind10: LessAgility	Lesser maneuverability and agility in auto driving mode of self-driving car as compared to standard car	2%	0%	3%	7%	16%	35%	37%	5.89	1.25

Ind11: FullControl	Computer will have full control over car	2%	2%	6%	12%	11%	25%	42%	5.70	1.51
Ind12: AnnMaint	Annual maintenance costs for a self-driving car may be a few hundred dollars more than for regular cars	1%	3%	7%	18%	19%	33%	19%	5.26	1.38
Ind13: LessSafe	A self-driving car might not be as safe as a standard car (the one you must operate)	20%	17%	14%	24%	11%	7%	7%	3.38	1.81
Ind14: TSP	A self-driving car can be synced with traffic lights and other vehicles to decrease travel time	0%	1%	4%	8%	20%	33%	32%	5.75	1.21
Ind15: Green	A self-driving car may generate less pollution compared to a standard car	1%	3%	6%	10%	21%	31%	28%	5.54	1.37
Ind16: MobForDisabled	A self-driving car can provide more mobility for someone with a physical, visual, or other forms of impairment	2%	2%	4%	9%	13%	37%	34%	5.75	1.37
Ind17: FriendRel	Reliable source of information: A friend/co-worker who has already purchased a self-driving car	0%	0%	1%	13%	27%	44%	15%	5.55	1.00
Ind18: Advt	Reliable source of information: Media Advertisements (Print, Television, Radio, Internet)	4%	13%	15%	24%	37%	5%	1%	3.98	1.34
Ind19: Dealer	Reliable source of information: Car dealer	8%	13%	16%	26%	26%	9%	1%	3.80	1.45
Ind20: PersonalResearch	Reliable source of information: Personal research	1%	0%	0%	4%	11%	46%	38%	6.13	0.94
Ind21: CarPrice	Importance of price of car in purchasing decision	5%	0%	0%	1%	8%	32%	54%	6.20	1.35
Ind22: CarQuality	Importance of car quality in purchasing decision	5%	0%	0%	0%	4%	27%	65%	6.38	1.31
Ind23: Environment	Importance of environmental impact in purchasing decision	5%	5%	4%	12%	28%	26%	19%	5.10	1.59

3. Modeling approach

We employed an ICLV modeling framework (Fig. 1) to capture the impact of peer social networks on an individual's likelihood to adopt CAVs. First, we performed an exploratory factor analysis (EFA) to identify attitudinal (latent) variables from the 7-level Likert scale variables (latent indicators in Table 4). Latent variables are then estimated through SEM, with a structural relationship with explanatory variables (Table 2 and Table 3) and a measurement relationship with indicator variables, assuming their error terms as normally distributed (an ordinal probit regression). DCM framework further utilizes the estimated latent variables along with the socioeconomic and household characteristics as explanatory variables with an ordinal dependent variable: likelihood to adopt a CAV (three levels: less likely, equally likely and more likely) (Section 2.2)" while assuming error terms as logistically distributed, i.e., ordinal logit (OL). Then we utilized Monte-Carlo simulation to estimate log-likelihood function, obtained as the probability of OL conditional on the probability of ordinal probit regression of latent variables and maximum likelihood estimator is used to maximize log-likelihood function. A reduced ordinal logit model (without any latent variables) was also estimated to compare the performance of the ICLV model.

3.1 Mathematical formulation

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

$$U_n = B\boldsymbol{x_n} + L\boldsymbol{x_n^*} + \varepsilon_n \tag{1}$$

$$\boldsymbol{x_n^*} = A\boldsymbol{x_n} + \gamma_n \tag{2}$$

$$\boldsymbol{i}_{\boldsymbol{nr}}^{*} = D\boldsymbol{x}_{\boldsymbol{n}}^{*} + \eta_n \tag{3}$$

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

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

Equation 1 represents structural equations for the DCM framework where U represents utility for each individual n ($n \in N$) explained by the vector $\boldsymbol{x}_{\boldsymbol{n}}$ ($K \times 1$) consisting of K observable explanatory variables presented in Table 2 and Table 3, vector $\boldsymbol{x}_{\boldsymbol{n}}^{*}(M \times 1)$ consisting of M unobserved latent variables identified from Likert scale variables in Table 5 and error terms ε_n, assumed to be independently and identically distributed (i.i.d.) logistically distributed with Σ_ε as the covariance matrix. B and L are the matrices with coefficients of explanatory variables ($1 \times K$) and latent variables ($1 \times M$).

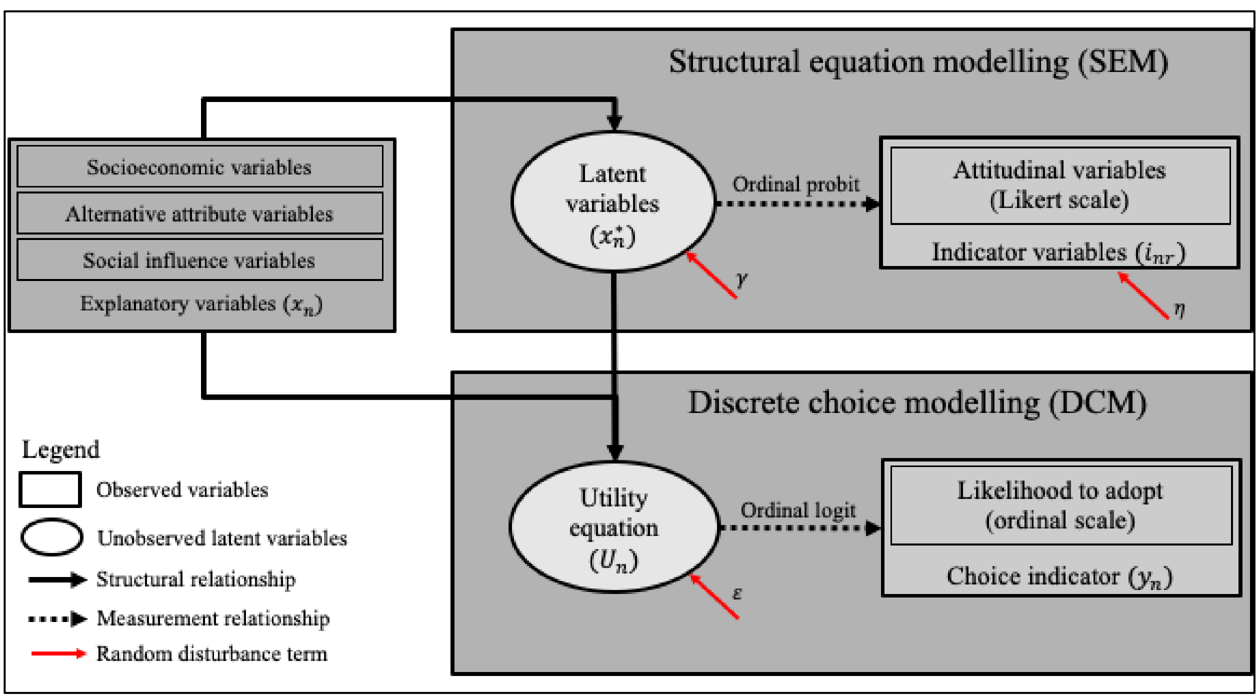

Fig. 1. Modeling framework: Integrated choice and latent variable model

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

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

Equation 5 represents the measurement equation for the DCM framework, based on ordinal logit kernel, as the dependent variable (Section 2.2), y, is categorical with three ordered categories (O) and measured from utility U, calculated in Equation 1, and certain thresholds μ_{O-1}.

3.2 Estimation and goodness of fit measures

ICLV models can be estimated in two steps, i.e., sequentially and simultaneously. In sequential estimation, the SEM framework is estimated first, which enables the flexibility of embedding the estimated latent variables into the DCM framework. Then DCM is estimated traditionally, maximizing the likelihood function conditional on explanatory and latent variables. In simultaneous estimation, both SEM and DCM modeling frameworks are estimated together where the likelihood function is conditional on the explanatory, latent, and indicator variables (estimating all the four equations 1 to 5 jointly) (Walker, 2001). Sequential estimation often results in inconsistent estimates with measurement errors due to the assumption of assuming latent variables as independent of the DCM framework. Simultaneous estimation resolves this limitation but at the expense of increased model complexity and computational effort. Although there is no statistical difference between results obtained from sequential and simultaneous estimations, the simultaneous estimation outperforms sequential estimation in model fitting (likelihood) and policy analysis, such as forecasting (Raveau et al., 2010). The main aim of this study is to identify the individuals' behavior towards CAV adoption based on their social networks; hence, we used simultaneous estimation. The likelihood function for simultaneous estimation is given by equation 6:

$$\begin{aligned}\mathcal{L}(y_n|\boldsymbol{x_n}, \boldsymbol{x_n^*}; B, L, \Sigma_\varepsilon, A, \varphi, D, \psi) \\ = \int_{x^*} f_y(y_n|\boldsymbol{x_n}, \boldsymbol{x_n^*}; B, L, \Sigma_\varepsilon) f_{i^*}(\boldsymbol{i_{nr}^*}|\boldsymbol{x_n^*}; D, \psi) f_{x^*}(\boldsymbol{x_n^*}|\boldsymbol{x_n}; A, \varphi) \mathrm{d}x^*\end{aligned} \tag{6}$$

Where first, second and third terms of integrand represent the density functions for the structural equation of DCM, measurement equation of SEM, and structural equation of latent variable, respectively. The joint probability of all three density functions is integrated over a vector of the latent construct x^* as the latent variables follow this distribution. The density function f_y is estimated as an ordinal logit kernel based on Equation 5. The integral is evaluated using the Monte Carlo simulation method, with 150 Halton draws from the normal distribution of latent variables $\boldsymbol{x}_{\boldsymbol{n}}^{*}$, and then the resulting likelihood is estimated using maximum simulated likelihood (MSL).

The main idea behind estimating an ICLV over traditional DCM is to improve the prediction of choice behavior (Vij and Walker, 2016) and goodness of fit measures vindicate any models' superiority when compared to other or reference cases in terms of fitting and prediction. ICLV models are becoming a preferred alternative to traditional DCM frameworks as they tend to fit and predict data better. Vij and Walker, (2016) compared ICLV models with the reference case DCM using simulations under different cases based on hypothetical datasets to vindicate the usability of former over latter. The authors conclude that ICLV models should only be preferred over the traditional DCM if they provide additional insights to the decision-making process, different interpretations of the estimates, and better model fit and prediction.

ICLV models are usually compared with their reduced form DCM frameworks, either including or excluding measurement indicators depending upon the objectives of the analysis. If the study objectives are to predict choice behavior under hypothetical conditions and indicator variables are expected to be absent in future analysis, it is a common practice to exclude measurement indicators from modeling framework to check its goodness of fit against the reference model (Ben-Akiva et al., 2002; Daziano and Bolduc, 2013; Yáñez et al., 2010), i.e., excluding density function of measurement equation of SEM in equation 6 and estimating DCM coefficient matrices B and L. Since the objectives of this study are to predict an individual's behavior towards adopting a CAV through the ICLV framework, we utilized the modeling approach proposed by Vij and Walker (2016) to check the goodness of fit of the estimated model against the reduced choice model. The reduced choice model is only the DCM part of ICLV, i.e., an ordinal logit without latent variables. Hence, removing latent variables $\boldsymbol{x}_{\boldsymbol{n}}^{*}$ from equation 1 will form the utility equation for the reduced choice model:

$$U_n = \mathrm{E}\boldsymbol{x}_{\boldsymbol{n}} + \epsilon_n \tag{7}$$

Equation 7 represents the structural equation for the reduced choice model framework where U represents utility for each individual n ($n \in N$) explained by the vector $\boldsymbol{x}_{\boldsymbol{n}}$ ($K \times 1$) consisting of K observable explanatory variables presented in Table 2 and Table 3 with E as the matrix of unknown coefficients. Error term ϵ_n, was assumed to be i.i.d. and logistically distributed with Σ_ϵ as the covariance matrix. The reduced choice model was estimated using equation 5 and maximum likelihood estimation for an ordinal logit framework. The goodness of fit measures of ICLV was compared with this reduced choice model to vindicate the superiority of the former.

4. Results

This section comprises the estimation results for the ICLV model in its two different components; SEM: measurement and structural equation models and DCM: ordinal logit with latent variables, along with the policy implications. A python-based software package, "PandasBiogeme" (Bierlaire, 2018), is used to estimate ICLV, where we first estimated the model sequentially and then used then simultaneously. The model was formulated using 70% of the dataset (N = 1,714), and the remaining dataset (N=735) was used for testing the model and keeping overfitting in check.

4.1 Exploratory factor analysis

We performed an EFA to identify the unobserved latent variables from the 23 indicator variables and yielded four factors. We used an R package "psych" (Revelle and Revelle, 2015) and Mplus to model EFA. First, we performed Bartlett's test of sphericity (Bartlett, 1950) and the Kaiser-Meyer-Olkin (KMO) test (Cerny and Kaiser, 1977) to check the sampling adequacy or factorability. We obtained significant results for Bartlett's test of sphericity (Chi-square value = 16,803.36 at p = 0.0) and KMO test (0.7037, which is more than the minimum threshold 0.6). To identify the number of factors, we performed scree plot analysis, based on eigenvalues, and based on the scree-plot (Fig. 2), we could choose seven factors as their eigenvalues were greater than one. We used varimax orthogonal rotation and maximum likelihood method for the EFA model after varying the number of factors from 1 to 7. Only four factors had a meaningful interpretation of relationships based upon the nature of questions asked and explained 41% of the cumulative variance in the sample. The model fit indices for four factors were: chi-squared statistic = 1226.86 (41 degrees of freedom at p-value = 0), root mean square residual (SRMR) =0.05, root mean square error of approximation (RMSEA) = 0.13 (90% CI = (0.124,0.136)) and comparative fit index (CFI) =0.887. The model is sufficient based on chi-squared statistic, SRMR (<= 0.08 as per Hu and Bentler (1999)), CFI (close to 0.90 as per Bentler (1990)). However, RMSEA =0.132 (<= 0.06 as per for good model fit as per Hu and Bentler (1999) and <= 0.10 for marginal fit as per Fabrigar et al. (1999)) and reflects a mediocre model fit (Fabrigar et al., 1999). However, Chen et al. (2008) evaluated the use of fixed universal cut off points for RMSEA empirically. They concluded that since population RMSEA is unknown to researchers, RMSEA should not be pursued as a single measure of fit based on the fixed cut-off, and there is a need for other goodness of fit measures. Also, the model shows an acceptable fit when CFI is greater than 0.90, while SRMR is less than 0.10 (Kline, 2015). Hence, Bartlett, KMO, chi-squared statistics, CFI (marginally close), and SRMR confirm the validity of the model.

We assume 0.4-factor loading as cut off values (Pituch and Stevens, 2015) for shortlisting the indicator variables based on their respective factors (bold values in Table 6). Based on the cut-off-values and explicit nature of indicator variables, identified four factors are named as Social Image (SI), CAV Barriers (CBa), CAV Benefits (CBe), and CAV Purchase (CP).

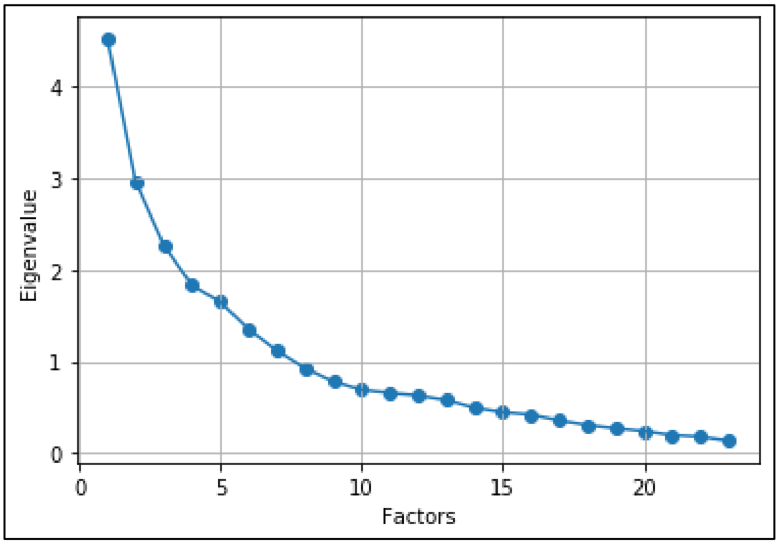

Fig. 2. Scree plot

The latent variable SI confirms an individuals' perception towards the impact of CAVs on their respective social status among peers and the importance of communication or input from their peer social network. For latent construct SI, among total five indicators; two indicators related to reliable information from advertisements (Ind18) and car dealers (Ind19) are excluded because of their irrelevance with an individual's social network as the importance of information obtained from advertisements and dealers is against the importance of status, work and non-work social network. The latent variable CBa contends an individual's perception towards anticipated barriers associated with CAVs such as the impact on CAV operation under poor internet connection, virus attack or system failure, computer's control over driving the car, and less maneuverability as compared to a standard car. Similarly, the latent variable CBe indicates the attitude towards the anticipated benefits of CAVs in terms of less pollution and providing mobility to disabled persons.

Some of the previous studies (Lavieri et al., 2017; Nazari et al., 2018) incorporated the green lifestyle in terms of the importance of living in a walkable neighborhood, close to transit, and close to the workplace (30-minute commute). Hence, we include Ind15 (CAVs less polluting than standard cars) to latent variable Cbe. The latent variable CP reveals the psychological constructs associated with the importance of price, quality, and environmental impact of CAVs in purchasing decisions. Also, the indicator variable Environment (Ind23) is related to two latent variables (CP and CBe). Since the associated survey question reflects impact on car purchasing decision, well supported by high loading in CP as compared to CBe, and is entirely different from green lifestyle as per previous studies (Lavieri et al., 2017; Nazari et al., 2018), we considered Ind23 in latent variable CP.

The estimation approach for the ICLV model, consisting of SEM and DCM, along with the structural and measurement relationships between observed explanatory variables, identified latent variables with their indicators and outcome variable along with their coefficient and random disturbance term matrices is portrayed in Fig. 3.

Table 6

Exploratory factor analysis results: latent variables (N = 1,714)

Indicator variable	**CAV Barriers**	**CAV Purchase**	**Social Image**	**CAV Benefits**
Ind01: PersonalImage			0.343	-0.116
Ind02: WorkSocialNetImp			**0.421**	0.117
Ind03: NonWorkSocialNetImp			**0.479**	0.101
Ind04: StatusImprove			**0.469**	
Ind05: LoseTies			0.313	
Ind06: PoorInternet	**0.567**	0.217		0.179
Ind07: TakeOver	**0.573**	0.266		0.172
Ind08: VirusAttack	**0.865**			
Ind09: SystemFailure	**0.853**			
Ind10: LessAgility	**0.611**			0.132
Ind11: FullControl	**0.452**			
Ind12: AnnMaint	0.299	0.109		0.214
Ind13: LessSafe	-0.335			0.101
Ind14: TSP	0.235		0.245	0.368
Ind15: Green				**0.913**
Ind16: MobForDisabled	0.245			**0.465**
Ind17: FriendRel			0.221	0.149
Ind18: Advt		-0.115	**0.775**	0.266
Ind19: Dealer	0.107	-0.16	**0.713**	0.198
Ind20: PersonalResearch	0.103	0.11	0.324	
Ind21: CarPrice	0.119	**0.826**		-0.119
Ind22: CarQuality	0.165	**0.917**		
Ind23: Environment		**0.696**		**0.508**

Hypothesis test: 4 factors are sufficient: chi-square statistic: 7,327.87 on 167 degrees of freedom at p-value : 0.

***Bold estimates: factor loadings greater than the cut-off value of 0.4**

4.2 Estimated SEM/latent variable model: impact of attitudes and perceptions on CAV adoption

The identified four latent variables are estimated based on observed explanatory variables and indicator variables with a structural relationship with socioeconomic and social influence variables. However, only for latent variable CP, in addition to socioeconomic and social influence variables, alternative attribute variables are also included in the structural relationship because of their similarity in capturing purchasing decisions. Model estimation results for the SEM framework for structural and measurement equation models are presented in Table 7 and Table 8, respectively. The model (presented in Table 7 and Table 8) resulted in Adjusted McFadden's ratio value of 0.167.

The estimated structural equation part of SEM (Table 7) confirms the relationship or effect of socioeconomic, social influence, and alternative attribute variables on perceptions about the social values (SI), CAV benefits, CAV barriers, and CAV purchasing characteristics (see eq (2)). We obtained significant relationships for all the latent variables except for CBe. For CBe, only household income of more than \$110,000 was significant at p-value <0.10. Compared to women, **men** are more concerned about their social values and less concerned about CAV barriers and CAV purchasing characteristics, if they are buying a CAV. **Individuals aged more than 54** years are uninterested in their social values and CAV purchase characteristics. Individuals with ethnicity as white are concerned about CAV purchase characteristics; African American individuals are concerned about CAV barriers when compared to other ethnicities. Also, individuals belonging to ethnicities other than white and black, are more concerned about their social values while purchasing a CAV but not concerned about CAV purchasing characteristics. As compared to faculties, **staff employees** are more concerned about barriers associated with CAV.

Adults with an annual remuneration of more than **$65,000** are negatively associated with the CAV purchase characteristics, whereas adults with annual income less than $35,000 are more concerned about the social values. This inverse relationship with social values can be attributed to respondents belonging to an educational institute. Hence, low income might represent staff employees and faculties, and researchers are generally unconcerned about their social image in an institutional environment. Hence, individuals with low personal income representing staff were positively related to social image.

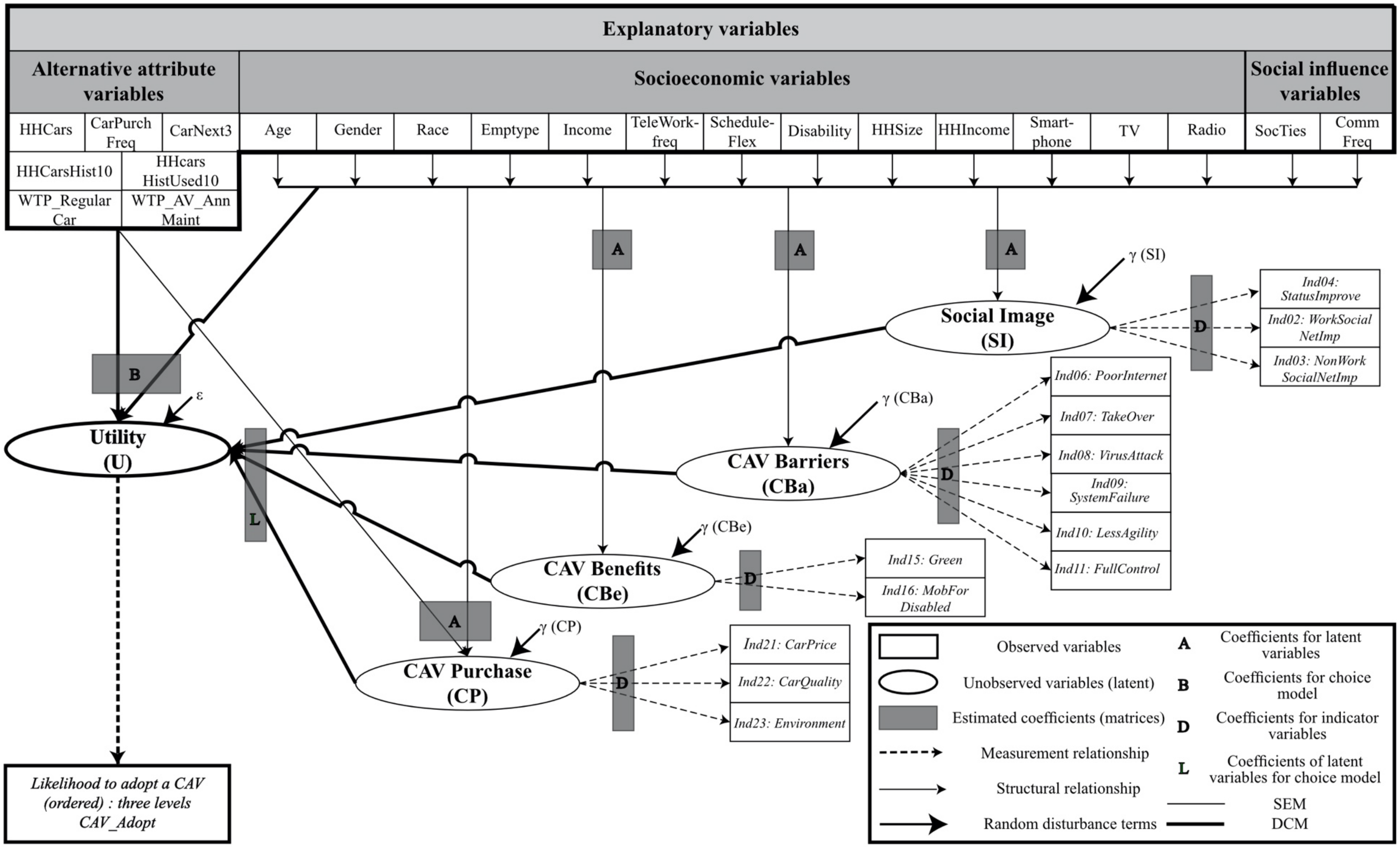

Fig. 3. Integrated choice and latent model: estimation framework

Households with a higher number of members are positively associated with the CAV's barriers and impact on social values but unconcerned about the purchasing characteristics. As expected, households with **high annual income** are not concerned about CAV purchasing characteristics. Individuals **frequently working from home** are not concerned about the impact of CAVs on their social status and CAV's potential benefits, probably as they do not travel to work every day; hence, they are uninterested in driverless capabilities and social values impact of CAVs. Adults with a flexible working schedule are more concerned about the CAV's purchasing characteristics. It can be attributed to their interest in traveling in a CAV during any time of day to attend meetings or workplace and hence are concerned about CAV purchase. As expected, physically challenged adults are concerned about social image and CAV purchasing characteristics because they will rely on CAVs to complete their traveling activities and will undergo a change in a social image with self-dependent mobility.

Adults owning a **smartphone or tech-savvy** lifestyle are unconcerned about any of the latent attitudes, which can be attributed to their awareness about the AV technology. Also, the individuals who purchased a car in the last ten years, buy cars frequently, willing to pay less for buying a standard car, and more for CAV maintenance and frequently communicate with social ties are unconcerned about the price, quality or environmental friendliness of CAVs. In terms of the impact of social networks on latent constructs, adults with a greater number of **social contacts** or ties are concerned about all the latent attitudes. This can be attributed to the transferred information about CAVs in their social network.

The estimated measurement equation part of SEM relates unobserved latent variables to the underlying indicator variables through an ordinal probit kernel through coefficient matrix D (see eq (3)) measured through eq. (4). All the coefficients are significant at the 0.05 level except for

CBe and reflect intuitive signs (Table 8). During estimation, for each latent variable, the intercept and coefficient of one indicator variable are kept as the base (zero) so that the other indicators can be interpreted with respect to the base indicator. Among three indicators of latent variable SSI the Ind04 is kept as the base indicator for indicators Ind02 and Ind03. Consequently, in CBa, Ind11 is kept as the base indicator for all other five indicators (Ind06, Ind07, Ind08, Ind09, and Ind10). For CBe, Ind16 is kept as the base for the Ind15. Finally, for CP, Ind23 is kept as the base indicator for two indicators Ind21 and Ind23. As per the base indicator in SI, the interpretation for the other indicators will be: if adults are concerned about their social values after buying a CAV, as compared to improve in status, they are more interested about the inputs from their work and non-work social networks which is not surprising as social values depend on the perceived social feedbacks.

If individuals are concerned about barriers associated with CAVs then as compared to giving up driving control to AV technology, they are positively associated with all other barriers like system failures - due to poor internet, virus attacks and system breakdown -, less maneuverability of CAVs as compared to regular car and need to take control from AV technology when required. The positive relationship of safety concerns with its indicators is in line with Nazari et al. (2018). This is not surprising as CAVs are not available in the market yet, and these are the anticipated potential barriers. There is no significant relationship between an adult's concern for the benefits of CAVs and its indicators representing benefits. As expected, if an individual is concerned about CAV purchasing characteristics, as compared to the environmental friendliness of CAVs, the individual is more interested in the price and quality of CAVs.

Table 7

Estimation results of SEM/ latent variable model: structural equation (N=1,714)

Explanatory variables		Coefficient (p-value)Significance			
		Social Image	CAV Barriers	CAV Benefits	CAV Purchase
Intercept		-1.55(0.502)	-0.644(0.125)	-0.092(0.999)	1.19(0.875)
Socioeconomic variables					
Age	Less than 40	--	--	--	--
	40 to 54	--	--	--	--
	more than 54	-0.545(0.01)**	--	--	-3.59(0.0)***
Gender (1 = male; 0 = female)		-0.545(0.009)**	-0.745(0.0)***	-7.1(0.436)	-3.29(0.0)***
Race	White	--	--	-3.55(0.445)	0.958(0.043)*
	Black or African American	--	0.443(0.0)***	--	--
	Others	1.46(0.0)***	--	--	-1.09(0.297)
Employee category (1= staff; 0 = faculty)		--	0.514(0.0)***	-5.26(0.388)	--
Approximate annual income	less than $35,000	1.57(0.0)***	--	--	--
	$35,000-$65,000	--	--	--	--
	more than $65,000	--	--	--	-2.73(0.0)***
Frequency of working from home	Frequent (once a week to daily)	-1.34(0.0)***	--	-4.37(0.335)	--
	Sometimes (Once in a month or year)	--	--	--	--

	Never	--	--	-3.83(0.414)	--
Flexibility in work schedule (1 = yes, 0 = no)		--	--	-1.26(0.531)	2.78(0.0)***
Any kind of disability which undermines driving (1 = yes, 0 = no)		2.46(0.0)***	--	2.63(0.467)	4.71(0.0)***
Number of household members		1.45(0.0)***	0.311(0.031)**	--	-1.58(0.076)#
Approximate annual household income	less than $65,000	--	--	--	-5.19(0.0)***
	$65,000-$110,000	--	0.429(0.0)***	--	--
	more than $110,000	--	--	-1.71(0.066)#	-2.55(0.0)***
Smartphone ownership (1 = yes, 0 = no)		-1.16(0.0)***	-0.246(0.191)	-7.27(0.456)	--
Listens to radio (1 = yes, 0 = no)		--	--	--	-2.77(0.022)*
Watches TV (1 = yes, 0 = no)		--	--	--	-2.74(0.024)*
Alternative attribute variables					
Number of owned cars (household)		--	--	--	--
New cars purchased over the last 10 years		--	--	--	-3.77(0.005)**
Used cars purchased over the last 10 years		--	--	--	2.78(0.006)**
Frequency of purchasing a car (household)	Frequently (once every 1 to 5 years)	--	--	--	-1.17(0.029)*
	Moderate (once every 10 years)	--	--	--	--
	Infrequent (once every 15 to 20 years)	--	--	--	3.66(0.0)***
Any plans to buy or sell a new car in the next 3 years (1 = yes, 0 = no)		--	--	--	1.68(0.002)**
	less than $15,000	--	--	--	-0.319(0.518)

Willingness to pay towards buying a regular car	$15,000-$30,000	--	--	--	--
	more than $30,000	--	--	--	--
Willingness to pay more towards maintaining a CAV than a regular car (annually)	Nothing or $0	--	--	--	--
	$0-$300	--	--	--	--
	more than $300	--	--	--	-2.82(0.0)***
Social influence variables					
Number of close social ties established at work		3.38(0.0)***	0.641(0.002)**	6.51(0.477)	6.96(0.0)***
Frequency of communication with social ties developed at work	Frequent (2-3 times a week to daily)	--	--	--	-2.48(0.0)***
	Sometimes (every couple of weeks to a month)	--	--	--	--
	Infrequent (once per month to every few months)	--	--	-3.19(0.226)	--
Goodness of fit measures:					
	Init log-likelihood:	-40840.44			
	Final log-likelihood:	-33916.19			
	Likelihood ratio	13848.5			
	Rho-square	0.17			
	Adj. Rho-square-bar	0.167			
	AIC	68078.38			
	BIC	68748.31			

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

Table 8

Estimation results of the latent variable model: measurement equation (N=1,714)

Indicator variables		Base indicator variable	Coefficient (p-value)[Significance]			
			Social Image	CAV Barriers	CAV Benefits	CAV Purchase
Ind02: WorkSocialNetImp	Intercept	Ind04: StatusImprove	0.334(0.27)			
	Coefficient		0.131(0.0)***			
Ind03: NonWorkSocialNetImp	Intercept		0.36(0.198)			
	Coefficient		0.121(0.0)***			
Ind06: PoorInternet	Intercept	Ind11: FullControl		1.02(0.001)***		
	Coefficient			0.497(0.0)***		
Ind07: TakeOver	Intercept			1.06(0.0)***		
	Coefficient			0.423(0.0)***		
Ind08: VirusAttack	Intercept			1.34(0.0)***		
	Coefficient			0.489(0.0)***		
Ind09: SystemFailure	Intercept			1.24(0.0)***		
	Coefficient			0.439(0.0)***		
Ind10: LessAgility	Intercept			0.773(0.0)***		
	Coefficient			0.342(0.0)***		

Ind15: Green	Intercept	Ind16: MobForDisabled	--
	Coefficient		--
Ind21: CarPrice	Intercept	Ind23: Environment	2.69(0.009)**
	Coefficient		0.13(0.0)***
Ind22: CarQuality	Intercept		3.25(0.005)**
	Coefficient		0.151(0.0)***

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

goodness of fit: same as SEM structural equation in Table 7

4.3 Estimated ordered logit model for levels of likelihood to adopt a CAV

We estimated the effect of explanatory variables over the likelihood of adopting a CAV with an ordinal logit framework with latent variables. In ICLV, the estimated latent variables from indicator variables along with the socioeconomic, alternative attribute, and social influence variables, contribute in predicting choice outcome, i.e., three levels of adoption likelihood incorporated into utility equation, used as explanatory variables along with the socioeconomic, alternative attribute, and social influence variables, (See eq. (1)) and then utility is measured through an ordinal logit framework (Eq. (5)).

We also removed the latent variables from the estimated ICLV model to formulate a reduced choice model (ordinal logit without latent variables) to compare the goodness of fit of both the models and check whether ICLV provides additional and better prediction of choice behavior. Also, in order to keep models comparable, we included all the variables of ICLV (present in structural equations of both SEM and DCM) in the reduced choice model. We also kept the insignificant variables in reduced ordinal logit to keep the difference between models as significant (Vij and Walker, 2016). We used equation 9 to calculate goodness of fit measures for ICLV, which are different from measures provided in Table 7 as the former does not include indicator variables (discussed in subsection 3.3). Table 9 delineates the AIC and BIC values for two models, and lower BIC values in the ICLV model vindicates its superiority in predicting the choice behavior over the reduced ordinal logit model.

Table 9

Model comparison: Reduced choice model vs. ICLV (N=1,714)

Fit index	Reduced choice model	ICLV
AIC	12,949.29	7,352.581
BIC	13,129.03	7,505.085

The model resulted in a cross-validation score of 76% (accuracy), which implies no overfitting on the training dataset. In addition to the accuracy, we also provide the confusion matrix for the ordered logit model with latent variables in Table 10 and Table 11. The model predicted less likely likelihood, most accurately followed by equally likely and more likely.

Table 10

Confusion matrix for ordered logit with latent variables (N=735)

Actual outcome \ Predicted outcome	Less likely	Equally likely	More likely
Less likely	219	61	0
Equally likely	40	258	14
More likely	4	56	83

The results for ordinal logit with latent variables for likelihood to adopt a CAV with three levels – less likely, equally likely, and more likely - are enumerated in Table 11. The sign of estimates can be interpreted as positive implies towards the highest level (more likely), and negative sign implies towards the lowest level (less likely).

Table 11

Classification report for ordered logit with latent variables (N=735)

	Precision	Recall	F1-score	Observations
Likelihood to adopt: less likely	0.83	0.78	0.81	280
Likelihood to adopt: equally likely	0.69	0.83	0.75	312
Likelihood to adopt: more likely	0.86	0.58	0.69	143
		Accuracy	0.76	

To answer our hypothesis of the **effect of social values** on the likelihood of adopting a CAV, the coefficient for the latent variable SI is negatively related. Therefore, if adults perceive that buying a CAV will increase their social image, they will be less likely to adopt the CAVs. To the best of our knowledge, we did not find any previous studies on the effect of social interactions on the likelihood to adopt, and our research is novel in this area. However, since CAVs are still in incipient stage and are not available in the market yet, this might be an explanation of less likely to adopt even if adopting would increase their social status (Leicht et al., 2018; Nordhoff et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018). Leicht et al. (2018) found a positive relationship of consumer innovativeness on social influence and purchase intention, and Panagiotopoulos and Dimitrakopoulos (2018) also found a positive relationship between social influence and intention to use. However, purchase intention is incomparable with WTP to adopt. Similarly, findings of Nordhoff et al. (2018) concluded social influence as the deciding factor in adopting CAVs.

Also, the likelihood to adopt is related negatively with latent variables CBa and CP, whereas there is an insignificant relationship with CAV Benefits. An interaction between **disability status** and latent variable **CBa** indicates that even if an individual is disabled and concerned about the barriers associated with CAV, the individual will still be less likely to adopt a CAV, which makes sense because of the incipient stage and barriers outweighing benefits of CAVs. Individuals' resistance to adopt CAVs because of the associated problems or barriers conform to the previous studies (Lavieri et al., 2017; Nazari et al., 2018). Since CAVs are not available in the market yet, hence CAV purchasing characteristics are related negatively with the likelihood of their adoption.

There is no significant effect of age and gender on adoption likelihood. However, individuals belonging to white ethnicity are less likely to adopt a CAV. As expected, **households with high incomes** are more likely to adopt CAVs, which is consistent with previous literature (Bansal et al., 2016; Bansal and Kockelman, 2018; Kyriakidis et al., 2015; Liu et al., 2019a; Shabanpour et al., 2018). Owning a smartphone has no impact on the likelihood of adopting CAVs. Also, as expected, if individuals purchased a new car in the last ten years, they will be less likely to buy a CAV as it will be too early for them to spend more money on buying another car.

Similarly, the frequency of purchasing a car is positively related to the likelihood to adopt a CAV as the less frequency implies buying a car equipped with the latest technology, which comes at high costs. In contrast, the high frequency may imply spending more amount of money once the existing car completes its lifetime (15 to 20 years). However, if an individual is interested in buying or selling a car in the next three years, he will be willing to pay less for a CAV, which can be due to the incipient stage of autonomous technology. WTP for the **annual maintenance** of a CAV has no significant impact on their adoption likelihood. If an individual is willing to pay a higher amount to buy a regular car, then the individual will be more likely to adopt a CAV, which can be attributed to added features in higher priced regular cars, which is analogous to vehicle automation features in CAVs. This finding is in line with Berliner et al. (2019). Social influence variables had no direct influence over choice outcomes and were removed from the model.

Table 12

Estimated ordered logit model (with latent variables) for capturing likelihood to adopt CAVs (N=1,714)

Explanatory variables		Coefficient (p-value)$^{\text{Significance}}$
Intercept		-2.78(0.658)
Socioeconomic variables		
Age	Less than 40	--
	40 to 54	--
	more than 54	-0.032(0.819)
Gender (1 = male; 0 = female)		--
Race	White	-2.62(0.0)***
	Black or African American	--
	Others	--
Employee category (1= staff; 0 = faculty)		0.436(0.379)
Approximate annual income	less than $35,000	--
	$35,000-$65,000	--
	more than $65,000	--
Frequency of working from home	Frequent (daily to once a week)	--
	Sometimes (Once in a month or year)	--
	Never	--
Flexibility in work schedule (1 = yes, 0 = no)		--
Any kind of disability which undermines driving (1 = yes, 0 = no)		-0.666(0.716)
Number of household members		--
Approximate annual household income	less than $65,000	--
	$65,000-$110,000	--
	more than $110,000	1.05(0.0)***
Smartphone ownership (1 = yes, 0 = no)		0.245(0.803)

Listens to radio (1 = yes, 0 = no)		--
Watches TV (1 = yes, 0 = no)		--
Alternative attribute variables		
Number of owned cars (household)		--
New cars purchased over the last 10 years		-0.535(0.032)*
Used cars purchased over the last 10 years		--
Frequency of purchasing a car (household)	Frequently (once every 1 to 5 years)	0.42(0.012)*
	Moderate (once every 10 years)	--
	Infrequent (once every 15 to 20 years)	0.78(0.0)***
Any plans to buy or sell a new car in next 3 years (1 = yes, 0 = no)		-0.608(0.0)***
Willingness to pay towards buying a regular car	less than $15,000	0.537(0.001)***
	$15,000-$30,000	--
	more than $30,000	0.632(0.001)***
Willingness to pay more towards maintaining a CAV than a regular car (annually)	Nothing or $0	-2.22(0.291)
	$0-$300	0.443(0.832)
	more than $300	2.0(0.344)
Latent Variables		
Social Image (SI)		-0.108(0.001)***
CAV Barrier (CBa)		-0.197(0.012)*
CAV Barrier * disabled		-2.81(0.0)***
CAV Benefits (CBe)		-0.187(0.138)
CAV Purchase (CP)		-0.057(0.006)**
Threshold 1		-0.056(0.993)
Threshold 2		3.854(0.0)***

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

goodness of fit: same as SEM structural equation in Table 7

4.4 Policy implications

This study highlights certain policy and practical implications. Such implications might provide useful insights about the role of consumer's attitudes, psychosocial factors, perceptions, and demographics towards CAV adoption in the form of their concern towards social values, benefits, barriers, and purchasing characteristics of CAVs to automaker industry and policymakers. We choose to describe such implications after scrutinizing the estimation results (Table 7 and Table 12) and marginal effects (Table 13) of ICLV model. The results of the latent variable model (Table 7) imply positive concern towards the different benefits and barriers associated with CAVs, which in turn affects consumers' trust in AV technology. Increased social influence, in the form of an increased number of contacts/ties, tends to make the individual more concerned about the quality, price, and environmental friendliness of CAVs. As far as barriers associated with CAVs are concerned, the positive impact of increased social ties can contribute to resolving them through proper information ways to overcome the barriers. For instance, if any individual is concerned about cybersecurity and privacy, advertising proper information regarding the anticipated precautions will help in resolving such concerns, which in turn will contribute to increased market penetration of CAVs. Technology savviness (smartphone ownership) is negatively related to attitudinal concerns. Hence, if a person owns a smartphone, then they do not care much about barriers associated with CAVs, which in turn will affect the likelihood to adopt CAVs.

Second, the results of ordinal logit model with latent variables (Table 12) imply that CAVs will have a positive impact on an adult's social network and are equivalent to a luxury car, however, less knowledge or exposure about AV technology makes the adult less likely to buy a CAV. AV technology and social interaction make it more evident for the consumer about the anticipated barriers outweighing benefits. Also, even if an individual is disabled and concerned about the problems of CAVs, the individual will still be less likely to adopt, which again highlights the importance of the adverse problems or barriers of CAVs, and these insights will help policymakers in overcoming all the barriers.

Third, we also choose to scrutinize the effect of change in different exogenous variables on the choice probability of adoption likelihood using marginal effects (Table 13). One unit increase in latent variable or perception about the impact on social values could increase and decrease both less and more likely levels by 3%. However, one unit increase in latent variable Social Image will decrease the equally likely likelihood by 25%. One unit increase in attitude towards CAV barriers could decrease an individual's likelihood of equally likely by 9%. One unit increase in perceptions towards the purchase characteristics associated with CAVs increases an individual's intention to equally and more likely to adopt a CAV by 5% and 43%, respectively. Hence, individuals who are equally likely to adopt a CAV has a high potential of shifting to less/more likely depending on the impact of CAVs on their concerns towards the social image, anticipated barriers and purchasing characteristics.

Hence the impact of social interaction, anticipated barriers, and purchase characteristics on the likelihood to adopt a CAV implies the dire need for future efforts in educating and informing potential consumers about the ways to solve anticipated problems can pave the way for increased CAV adoption. Individuals' susceptibility towards purchase characteristics of CAVs implies the need to advertise or disseminate information about the attractive features of CAVs to the general public. Hence, automakers and policymakers will need to be wary about these characteristics of CAVs to increase their market penetration. Therefore, policies targeting awareness and educating the consumers with the technological benefits of CAVs will be beneficial for increased CAV adoption in its early stages.

Table 13

Estimated marginal effects for ordered logit model (with latent variables) for measuring individual's likelihood to adopt a CAV (N=1,714)

Explanatory variables		**Willingness to pay**		
		Less	**Moderate**	**More**
Socioeconomic variables				
Race	White	**0.0490**	**-0.2983**	**-0.4978**
	Black or African American	--	--	--
	Others	--	--	--
Approximate annual household income	less than $65,000	--	--	--
	$65,000-$110,000	--	--	--
	more than $110,000	-0.0054	0.0269	0.0896
Alternative attribute variables				
New cars purchased over the last 10 years		0.0129	-0.0810	-0.1161
Frequency of purchasing a car (household)	Frequently (once every 1 to 5 years)	0.0022	-0.0123	-0.0297
	Moderate (once every 10 years)	--	--	--
	Infrequent (once every 15 to 20 years)	-0.0099	0.0169	0.3383
Any plans to buy or sell a new car in the next 3 years (1 = yes, 0 = no)		0.0149	-0.0759	-0.2330
Willingness to pay towards buying a regular car	less than $15,000	0.0001	-0.0007	-0.0012
	$15,000-$30,000	--	--	--
	more than $30,000	**-0.0009**	0.0043	0.0166

Latent Variables			
Social Image	0.0319	-0.2478	-0.0313
CAV Barrier	0.0120	-0.0942	-0.0043
CAV Purchase	-0.0174	**0.0593**	**0.4312**

*** Bold estimates indicate maximum and minimum**

5. Conclusions

In this paper, we propose to contribute to identifying the relationship of individuals' socioeconomic characteristics, vehicle ownership, attitudes, and perceptions towards CAVs with the anticipated likelihood to adopt CAVs. We are contributing in terms of studying the effect of an individuals' social network or values on their behavior towards adopting CAVs. To achieve this, we utilized an integrated choice and latent variable (ICLV) modeling framework based on an institutional dataset. First, we performed an exploratory factor analysis to identify the psychosocial and attitudinal constructs. Then we estimated the ICLV modeling framework to estimate the impact of identified attitudinal concern on likelihood towards CAV adoption. We also modeled a reduced choice model (ordinal logit without latent variables) to compare the performance of ICLV.

Results revealed four attitudinal variables reflecting the importance of social values and CAV characteristics like benefits, barriers, and purchase attributes while purchasing a CAV. ICLV framework outperformed ordinal logit without latent variables in terms of increased likelihood and behavioral interpretation of attitude and perceptions. Results revealed a positive impact of adopting CAVs on the social values of an individual. Households with high annual income, willing to pay more to buy a regular car and frequent car buyers are more likely to adopt CAVs. Individuals are less likely to adopt a CAV if they are concerned about associated barriers and purchasing characteristics of CAVs. Besides, technology savviness was related negatively with perception towards the social image on adopting a CAV.

This study includes limitations in terms of the sampling frame (institutional audience as target population), cross-sectional stated preference survey including only personally owned CAVs as mode choice, and synthetic population. The dataset used in this study did not consider any questions about shared autonomous vehicles (SAVs); study scope is limited to personally owned CAVs and educational institute synthetic population. Future research directions with a survey covering respondents with the general population with owned and shared CAVs will further bolster policy implications. The target population in this study is an institutional audience, and since such an audience is more exposed to technological innovations at an early stage and often interacts with their colleague researchers involved in such technological innovations, their preferences towards CAVs will provide the automakers key takeaways for pricing and advertising such vehicles. Hence, the findings of this study will provide key insights to the policymakers, automakers, and planners to identify the factors affecting the price of CAVs, including the peer social network interaction, and frame or implement policies/plans accordingly. The study results should be considered with some caveats as the findings are based on a population with certain employment types in a university context and not from a general population.

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