How Do Safety Perceptions and Car Dependency Affect Autonomous Vehicle Adoption?

Parastoo Jabbari

Department of Civil and Environmental Engineering
University of Washington
119 More Hall, Box 352700
Seattle, WA 98195-2700
Email: jabbari@uw.edu

Don MacKenzie

Department of Civil and Environmental Engineering
University of Washington
201 More Hall, Box 352700
Seattle, WA 98195-2700
Tel: 206-685-7198; Email: dwhm@uw.edu

Word count: 6100 words text + 5 tables x 250 words (each) = 7350 words

Submitted August 1, 2020

ABSTRACT

In this study, we explicitly modeled how the public's perceived automated vehicle (AV) safety and their psychological attachment to cars affect mode choices involving privately owned self-driving cars and driverless ride-hailing services. We adopted psychometric questions developed by Ge et al. *(1)* to capture these two latent variables and designed a stated preference survey based on the participants' actual travel patterns. Then, we incorporated latent variables in a mode choice model and quantified their impact on mode choices using an integrated choice and latent variable model (ICLV). We found that both latent variables have a statistically significant effect on mode choices. The results show that car dependency has the most potent effect on privately owned cars (e.g., regular car and self-driving car), followed by driverless ride-hailing and regular ride-hailing. We also found that changes in safety perception have a sizeable monetary equivalent. We further investigated the impact of improvements in safety perception through four scenarios. The scenario testing results show that as the distribution of perceived safety is compressed toward positive safety perception, the market share of AVs spikes and dominates regular cars. Our results demonstrate that based on the current public's understanding of AVs, even if AV prices are comparable to regular cars, we cannot expect widespread use of AVs. However, improvements in AVs' safety and, consequently, consumer safety perception can considerably expand AVs' market share, and it may offset the high cost of using the technology.

Keywords: Self-driving car, integrated choice and latent variable, mode choice, perceived safety, car dependency

INTRODUCTION

Over the past decade, the potential benefits of automated vehicles (AVs) and services have been explored by many researchers (For example, Fagnant and Kockelman, *(2)*; Wadud et al., *(3);* Litman, *(4)*). These benefits include but are not limited to, reducing human error-induced crashes, improving congestion, enabling persons with reduced mobility (e.g., elderly, disabled), lowering energy consumption, and reducing carbon emissions. Despite potential long term merits of AVs, studies have identified several barriers for the public's acceptance and adoption of AVs. Safety of AVs is one of the main obstacles that frequently comes up in the literature. Even though AVs are expected to be safer than cars driven by humans, current assessments of people's willingness to use AVs or to ride in driverless ride-hailing services are affected by people's lack of trust in AV technology and a recognition that the technology is not yet ready for the market. For example, an international survey of 1,722 residents of six countries found that the majority of respondents are highly concerned about "equipment or system failure" and "self-driving cars not performing as well as human drivers" *(5).* Another paper studying public acceptance of AVs found that out of 467 study participants, 82% ranked "personal safety and the safety of those around you while operating an autonomous car" as the most critical topic affecting their adoption of AVs *(6)*. Xu et al. *(7)* found that perceived safety of AVs can predict intentions to use and willingness to ride in an AV, while Nazari et al. *(8)* and Mushtaq et al. *(9)* confirmed that safety concerns adversely impact public acceptance of shared and regular self-driving cars.

Additionally, despite similarities in the in-vehicle experience of AV mobility services (e.g., driverless ride-hailing) and privately owned AVs, studies show that the public perceives them differently, and willingness to use them varies among different groups of individuals. For example, an online survey of 556 residents of Austin metropolitan showed that most of the respondents prefer to own an AV rather than use AV services such as driverless ride-hailing *(10)*. Another study has identified that younger, more educated, technology savvy and urban residents are more likely to use AV mobility services than older individuals and residents of suburbs and rural areas *(11)*. Krueger et al. *(12)* surveyed 435 residents of Australia's metropolitan areas and found that people who use multiple modes in their daily lives are more likely to use AV services. Very few studies have explored the underlying reasons for these differences. One study found that individuals who express greater concern for the environment are more likely to use shared autonomous vehicle services *(13)*.

In this study, we hypothesized that willingness to use mobility services is likely affected by psychological attachment to car ownership. We explicitly model how safety perception and car dependency affect mode choices involving AVs and driverless ride-hailing services using an integrated choice and latent variable model (ICLV). We incorporated these two constructs as latent variables into a mode choice model.

In the past few years, more studies have investigated latent variables, such as people's perceptions and attitudes toward AVs and services, to better understand AV adoption motivations and barriers. For example, Haboucha et al. *(13)* explored the motivations of travelers to adopt AVs and modeled mode choices between regular cars, privately owned AVs, and shared AVs. They identified five latent variables using identifier questions from prior literature and found three of them statistically significant in the mode choice model: 1) Pro-AV attitudes, 2) enjoyment of driving, and 3) concern for the environment. As expected, their results show that people who enjoy driving are more likely to use a regular car than an AV, and individuals with pro-AV attitudes are more inclined toward AVs. Concern for the environment was a more robust predictor for shared modes. Lavieri and Bhat *(14)* explored which individuals are willing to share an AV with strangers in the future using a multivariate integrated choice and latent variable approach. Their model included three latent variables: privacy-sensitivity, time-sensitivity, and interest in the productive use of travel time. They concluded that individuals who are more interested in using travel time productively are more likely to choose ride-hailing services. They also found that travelers dislike shared ride delays more than the presence of strangers. Wicki et al. *(15)* investigated the willingness to pay and use self-driving bus services. They incorporated technology-related attitudes to explore the tradeoffs between "technological skepticism" and the potential benefits of the service. They found that the technology acceptance latent variable is a strong predictor of self-driving bus usage. Rahimi et al. *(16)* analyzed people's attitudes toward shared mobility options and autonomous vehicles using a structural equations model. They identified eleven latent variables and explored latent variables relationship with socioeconomic characteristics and correlations between the attitudes.

Ge et al. *(1)* reviewed the transportation literature and concluded that processes of selecting questions to measure psychological constructs are inconsistently applied, and in many cases, questions are somewhat arbitrarily defined. Therefore, they conducted an extensive literature review to identify the critical psychometric measures influencing mode choices and specifically, adoption and use of autonomous vehicles. They considered three psychological concepts (norms, perceptions, and attitudes) and nine qualitative utility constructs that shape individuals' travel behavior to develop a comprehensive list of latent variables. They performed a factor analysis on a nationwide sample to obtain a minimum set of latent variables and questions to measure them. The factor analysis results identified nine latent variables and 44 questions.

In this study, we adopted questions identified by Ge et al. *(1)* for the safety of AVs and car dependency latent variables. Then we investigated and quantified the impact of psychological constructs on mode choices, specifically choices involving privately-owned AVs and driverless ride-hailing services. To improve behavioral realism, we designed a novel stated preference choice experiment based on each user's revealed preference data *(17)*. We asked respondents to choose from a choice set that included both traditional modes (e.g., car, bike, transit, and walking) and unconventional modes (e.g., ride-hailing, privately owned self-driving car, driverless ride-hailing service) since such a mixed choice set is more likely in the next few decades *(4)*. An ICLV model was built using Biogeme software *(18)* to analyze the data. In the following paragraphs, we further discuss ICLV models and relevant transportation literature using these models.

Traditional discrete choice models treat the decision-makers as an "optimizing black box" and have focused on observable variables such as attributes of alternatives, socio-economic characteristics of decision-makers, market information, and past experiences as inputs that can determine choice *(19)*. However, findings from studies in the social sciences have shown that latent constructs such as attitudes, norms, and perceptions can override the influence of observable variables of disaggregate behavior *(20, 21, 22, 23)*. Figure 1 illustrates the decision-making process. Terms in rectangles can be observed or measured by proper experiments. Terms in ovals are unobservable latent variables. Perceptions, generalized attitudes, preferences, decision protocols, and behavioral intentions are essential constructs in the modeling of cognitive decision process *(19)*. Although these latent constructs cannot be measured directly, latent variable modeling techniques hypothesize that their effects on measurable variables can be observed and measured *(24)*.

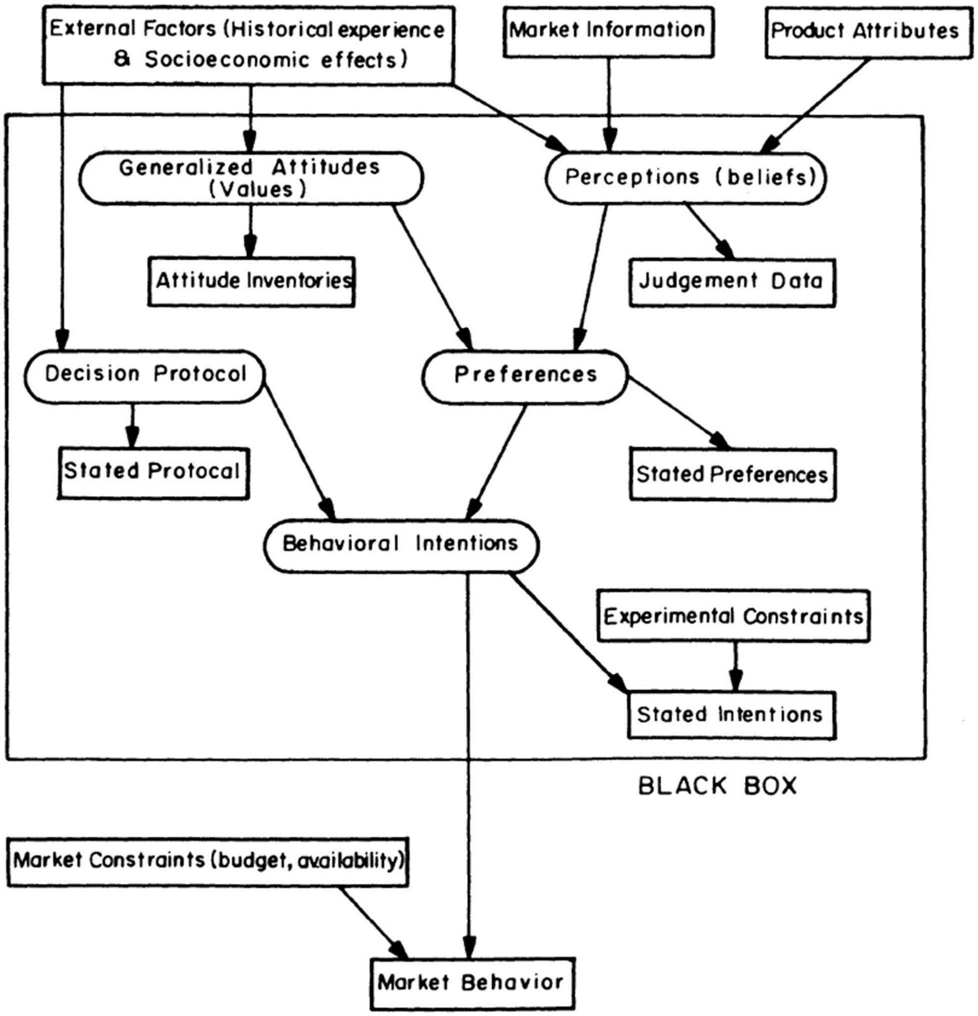

Figure 1 Path diagram for the customer decision process (McFadden, 1986)

ICLV models are an extension of traditional discrete choice models that fall under the broader umbrella of hybrid choice models (HCMs). ICLV models explicitly incorporate psychological factors such as attitudes and perceptions into choice model, and model the cognitive processes underlying the formation of a choice *(20, 24)*. ICLV models include a choice model formulation that contains unobserved psychometric measures (e.g., attitudes and perceptions) incorporated through latent variables, along with observed variables. Perception variables capture how decisionmakers perceive attributes of different alternatives. Attitudes reflect decisionmakers' tastes, needs, goals, and capabilities that have been shaped over time and are impacted by both experience and factors such as their socioeconomic characteristics *(25)*.

Bolduc and Daziano *(25)* described the estimation techniques and implementation of ICLV models using empirical data. They showed that estimating ICLV models using simulated maximum likelihood can be successfully implemented. They concluded that the ICLV model provides an "unbiased, consistent, and smooth estimator of the true probabilities." Their case study showed that the ICLV model could be adopted for practical situations and improve understanding of consumer profiles and new technology adoption.

Vij and Walker *(20)* evaluated the ICLV modeling framework's statistical properties and compared them to a reduced form choice model without latent variables. They found that ICLV models do not offer improvements in terms of goodness-of-fit and the consistency of parameter estimated over the reduced form choice models. However, ICLV models allow identification of structural relationships between observable variables that could not be identified using choice models without latent variables. They also found ICLV models are potentially more efficient in estimating parameters than reduced form choice models without latent variables.

Applications of ICLV models in transportation and specifically mode choice studies have been growing over the past two decades. For example, Morikawa et al. *(26)* included comfort and convenience latent variables in their study of mode choice. They found integrating latent variables improves goodness-of-fit, and both latent variables are significantly positive. Johansson et al. *(27)* included latent variables for attitudes towards flexibility and comfort, and for being pro-environment, in their mode choice model. They found that both influence mode choice decisions. They concluded that in addition to economic incentives, there are other ways to attract individuals to different modes of transportation. Ding et al. *(28)* compared the ICLV model with the traditional model and explored the influence of attitudes toward active modes on mode choices. They found that the ICLV model outperforms traditional models in terms of fit and explanatory power, and attitudes toward active modes play an essential role in the nonmotorized mode choice. Bouscasse *(29)* has conducted an extensive literature review of ICLV models' applications in mode choice modeling. They concluded that even though forecasting is difficult when using ICLV models, ICLV models are useful for informing policy development and recommendations.

In the following sections, we first discuss the collected data and characteristics of our sample. Then we talk about the applied methods and results. The paper concludes with a discussion of the results and suggestions for future work.

DATA

We designed a survey that consisted of four sections: 1) socio-economic questions, 2) trip diary, 3) choice experiments, and 4) psychometric measures. Section one included questions about the respondents' socio-economic characteristics, and their household. In section two, the respondents filled out a trip diary for each trip that they made during their typical or most recent working day, including the approximate origin and destination addresses and the purpose of the trip. Approximate addresses were used in real-time to retrieve travel time, wait time, and cost data the Google Distance Matrix and Uber APIs. In section three, API data was used as base values to generate personalized choice scenarios for the respondents. Section four included the psychometric questions prioritized by Ge et al. *(1)*.

For the attributes that were not collected through APIs, we assumed the following base values:

- Transit waiting time of 10 minutes; Transit wait time is derived based on average weighted transit wait times in 2017 National Household Travel Survey, which is 9.6 minutes *(30)*.

- Parking fee of $2.00 per hour; Auchincloss et al. *(31)* used 2009 survey of public parking agencies and found that on average, on-street meters charges $1 per hour. Considering this value in 2009, we decided to use $2.00 per hour for our survey.

- Monthly car payment of $500 (for self-driving cars; and regular cars when individual does not own a car). Experian data from first quarter of 2019 *(32)* shows an average monthly payment of $554 for new cars.

We collected travel time for all the modes (driving, ride-hailing, transit, walking and biking) and travel cost for transit from the Google Distance Matrix API; and collected wait time and travel cost for ride-hailing trips from the Uber API. Since for ride-hailing option there is no intermediate stops we assumed ride-hailing in-vehicle travel time is the same as the driving time collected from the Google API.

To identify the sensitivity of respondents' choices to different attributes, we multiplied the base values of attributes by multipliers shown in Table 1. The set of multipliers used in any choice situation was determined by an experimental design. The product of the base value and the multiplier was then included in the choice scenarios. More details about experimental design can be found in Jabbari et al. *(17)*.

TABLE 1 Experimental attribute levels

Attribute	Levels					
Transit Travel Cost	-	0.6	0.8	1	1.2	1.4
Ride-hailing Travel Cost	0.2	0.6	0.8	1	1.2	1.4
Parking fee	-	0	0.6	1	1.4	-
Travel time	0.6	0.8	0	1.2	1.4	-
Wait time	-	-	0.6	1	1.4	-
Monthly payment	-	0.6	0.8	1	1.2	1.4

In section three, respondents faced six personalized choice scenarios based on the trip diary and API data. Respondents were asked to make travel-related decisions (e.g. purchase a self-driving car, purchase/sell a car, choose a mode) for a hypothetical individual who was very similar to them in terms of age, gender, and vehicle ownership. This approach is inspired by Le Vine et al. *(33)*. Polman *(34)* found that individuals are more inclined to justify choices made on behalf of others than the ones they made for themselves. Each person participated in six choice experiments, and out of those, the first two were simpler and were used to familiarize them with the format, and the last four were used for modeling. The choice set included seven modes: regular car, self-driving car, ride-hailing, driverless ride-hailing, transit, bike, and walk. More details about the survey are presented in Jabbari et al. *(17)*.

The survey was programmed and hosted online, and Amazon's Mechanical Turk (MTurk), a crowdsourcing marketplace platform, was used to recruit survey participants. 1000 respondents were recruited in the U.S. To check the quality of responses, we repeated two of the psychometric questions and reversed the order of the Likert scale choices. Responses meeting any of the following criteria were flagged and responses with two or more flags were omitted from the sample.

- Responses to the repeated psychometric questions that differed by more than one point on the six-point Likert scale.

- Number of children they entered exceeded the number of household members.
- Purchase year of their car was more than one year before the model year of the car.

Individuals who did not provide their approximate address or entered an address that did not exist (and as a result API data for them were not accurate), were removed from the sample. We also removed individuals whose trips were too long (driving time more than 2.5 hours) or too short (driving time less than 5 minutes) to be of interest in this work. After cleaning the data, 757 respondents (out of 1000) were approved, and their corresponding data were used for analysis.

89% of our sample indicated that they are full time employees. The sample's household income distribution is shown in Figure 2. Both mean and median income fall into the $40,000-$59,999 category. In 2018, median household income for the United States was $61,937 *(35)*.

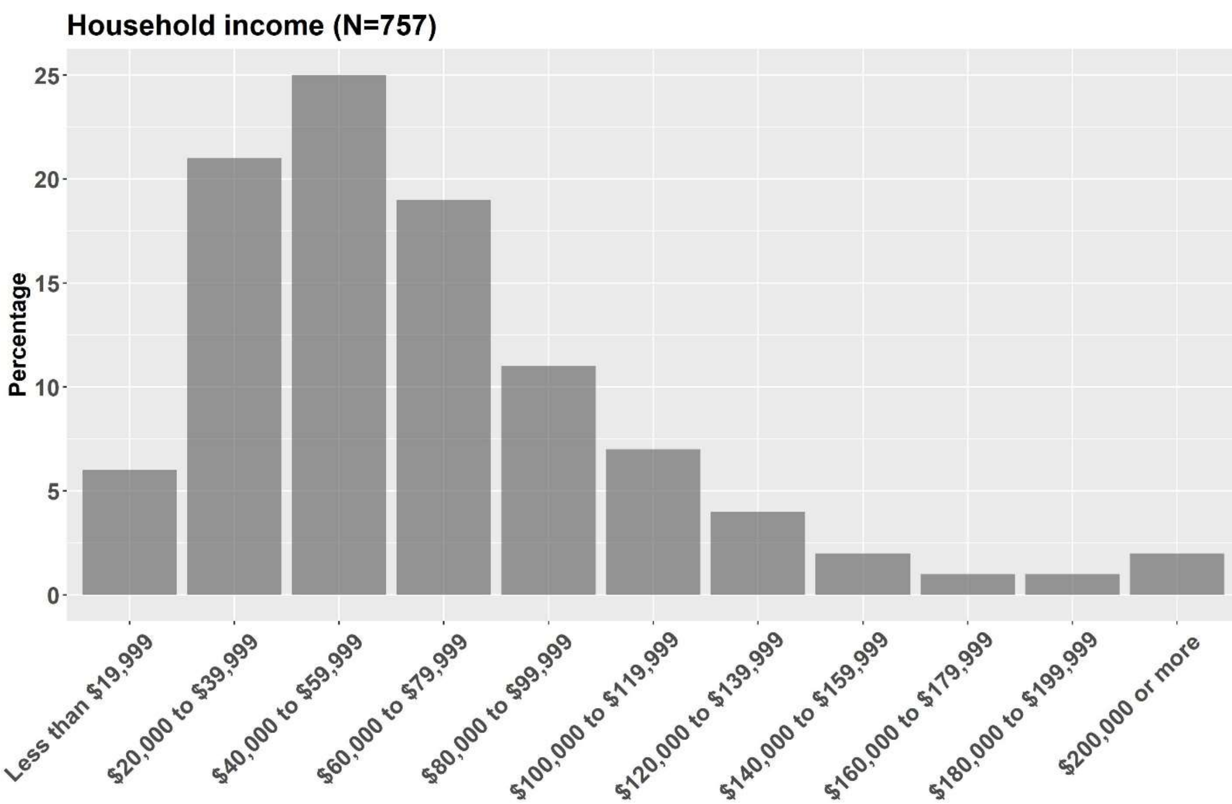

Figure 2 Sample's household income

Our sample consists of 46% females, 53% males, and 1% who chose other. Compared to the U.S. population (51% females, 49% males *(36)*), our sample represents more men. Figure 3 shows the educational attainment of the sampled individuals which is skewed toward higher education than the U.S. population *(37)*.

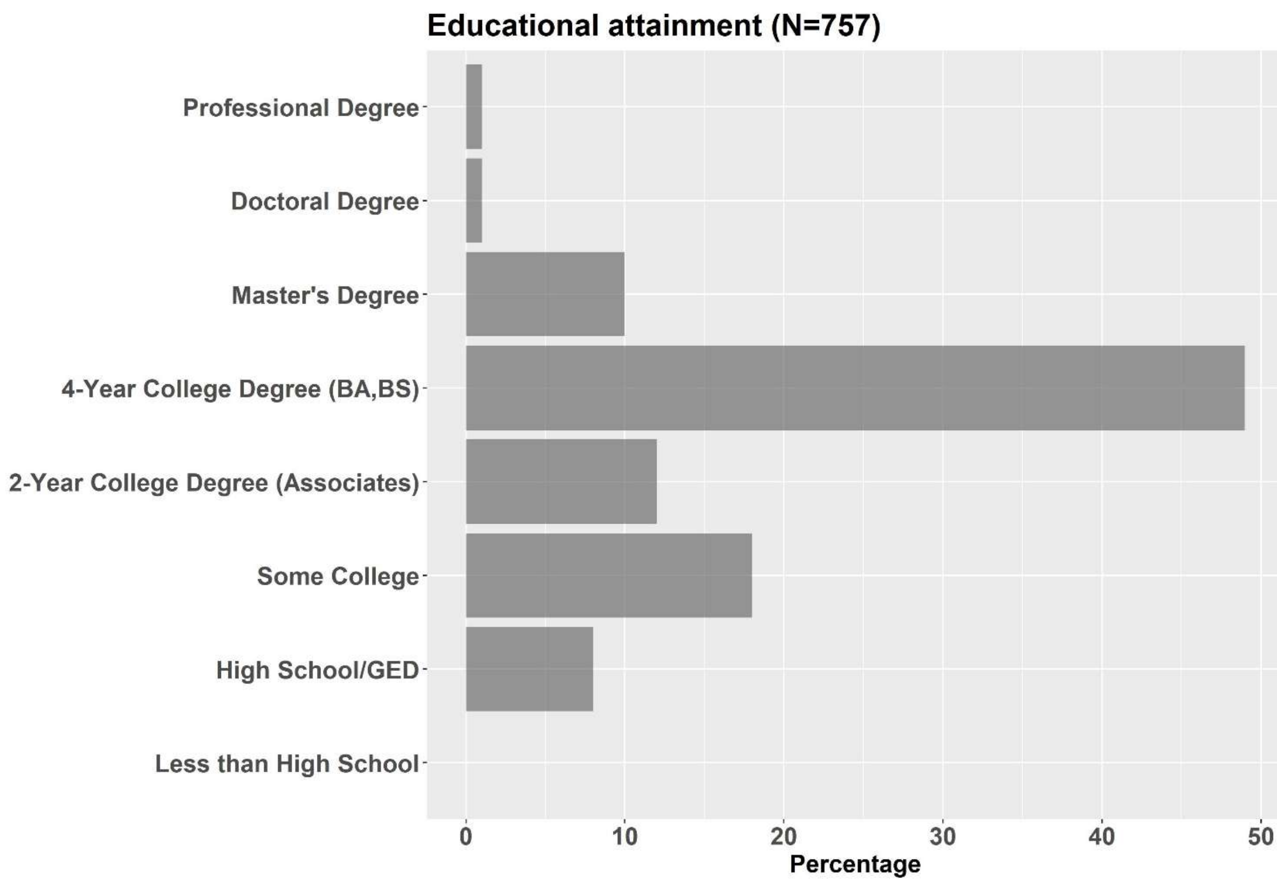

Figure 3 Sample's educational attainment

Figure 4 shows the age distribution of our sample. The mean and median age are 33 and 35 years old, respectively. The median age of individuals 18 and older in the U.S. is in the 45-49 years old range *(38)*. Our sample is biased toward younger individuals compared to the national population

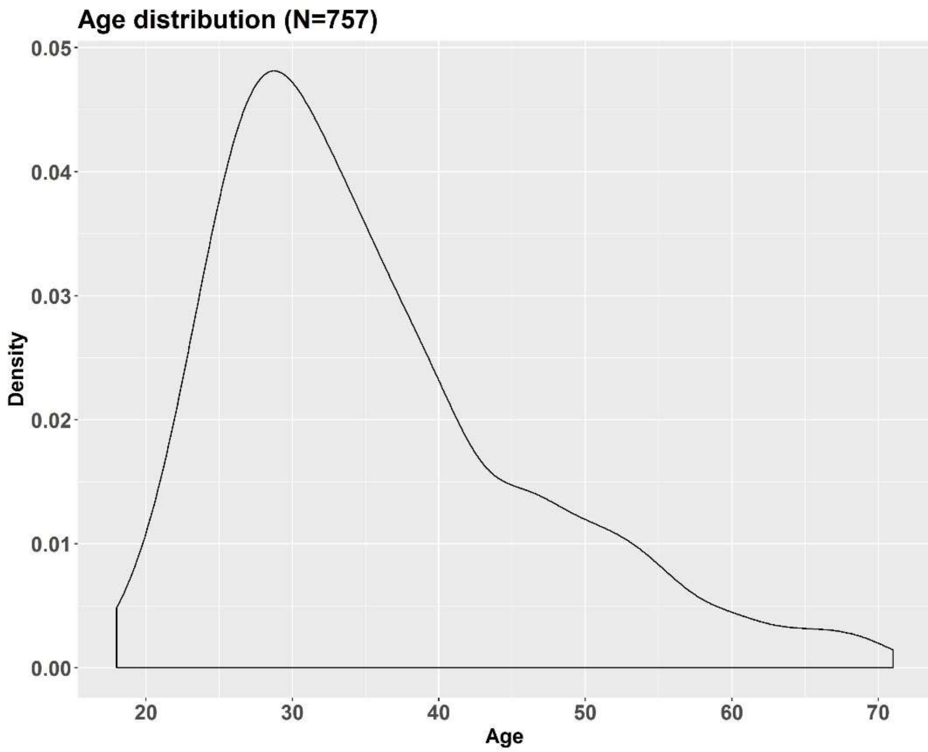

Figure 4 Sample age distribution

METHODS

Figure 5 depicts the ICLV framework we adopted for this study. There are two main components: (1) a discrete choice sub-model and (2) a latent variable sub-model. Each of the sub-models includes a structural and a measurement component *(20)*. Under the random utility maximization (RUM) framework, the standard choice model is a latent variable model itself. Utility is a latent construct that measures an individual's satisfaction conditional on attributes of each alternative. Structural equations describe the latent variables in terms of observable exogenous variables, and measurement equations link latent variables to indicators. For the latent variable sub-model, indicators can be responses to psychometric questions. For the choice model, the indicator is the decision maker's choice (whether revealed or stated) *(20, 25)*.

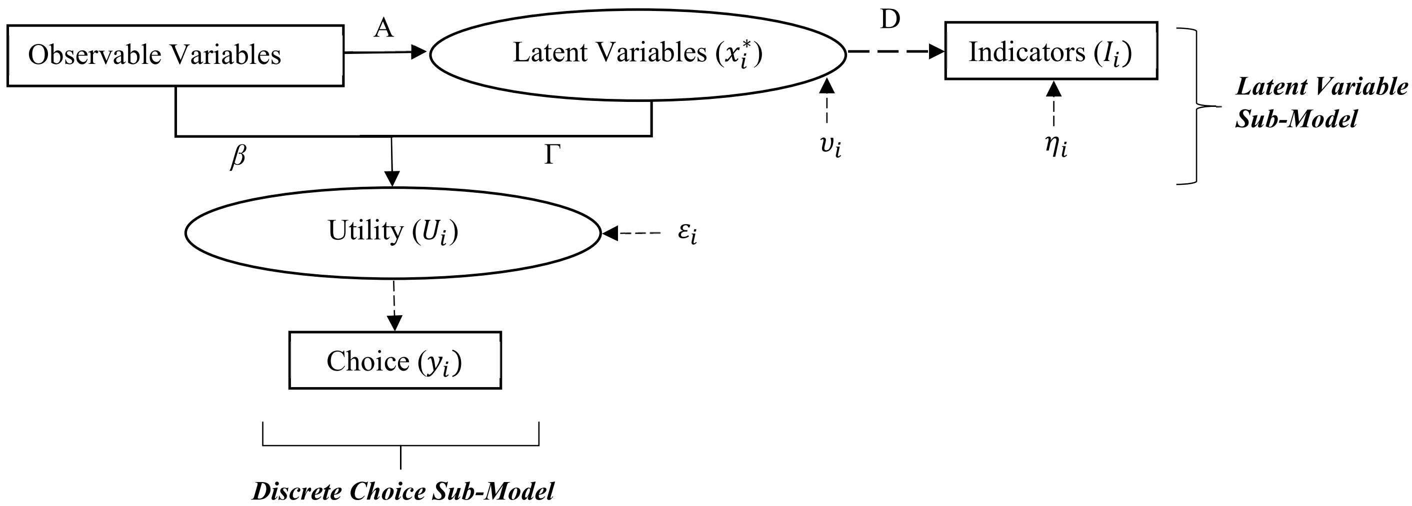

Figure 5 The ICLV framework (adopted from Vij and Walker *(20)*)

We adopted Vij and Walker's *(20)* ICLV model representation as follows:

Structural equations

$$U_i = \beta x_i + \Gamma x_i^* + \varepsilon_i \quad (1)$$

$$x_i^* = A x_i + \upsilon_i \quad (2)$$

Measurement equations

$$I_i = D x_i^* + \zeta_i \quad (3)$$

$$y_i = \begin{cases} 1 \; if \; u_{ij} \geq u_{ij'} \; for \; j' \in \{1, \ldots, J\} \\ \quad 0 \; otherwise \end{cases} \quad (4)$$

Where U_i is the $(J \times 1)$ vector of utilities of each of the J alternatives for the decision-maker i, x_i is the $(K \times 1)$ vector of observable explanatory variables and $x_i^*$is the $(M \times 1)$ vector of latent variables, β and Γ are the $(J \times K)$ and $(J \times M)$ matrices of unknown model parameters corresponding to observable and latent variables, respectively. ε_i is the $(J \times 1)$ vector indicate the error terms associated to utilities; A is the $(M \times K)$ matrix of parameters that indicate the structural relationship between the latent and observable variables. υ_i is the $(M \times 1)$ vector of stochastic component of that relationship. I_i corresponds to a $(R \times 1)$ vector of indicators used to measure the latent variables for the decision-maker i. D is the $(R \times M)$ matrix of unknown parameters that indicate the relationship between indicators and latent variables, and ζ_i is a $(R \times 1)$ vector of measurement equations error terms; y_{ij} is the choice indicator

(20). More details on theoretical concepts can be found in Vij and Walker *(20)* and Bolduc and Daziano *(25)*.

RESULTS

We conducted a confirmatory factor analysis and confirmed the relationship between indicator questions and latent variables developed by Ge et al. *(1)* in our data. In our model each individual can have up to four choice scenarios and we captured the repeated observation nature of the data through random effects. For each individual, we considered their first trip of the day mode choice for modeling.

We found the safety of AVs and car dependency variables were statistically significant and they improved the explanatory power of the model. Safety of AVs was included in self-driving car and driverless ride-hailing modes. For car dependency, we estimated three coefficients: one for privately-owned options, one for driverless ide-hailing, and another one for regular ride-hailing option.

To estimate the random effects, we used 2500 Halton draws taken from a normal distribution.

The utility equations for self-driving car and driverless ride-hailing alternatives are given by:

$$U_{Self-driving\ car,i} = V_{Self-driving\ car,i} + \Gamma_{SP} SP_i + \Gamma_{CD,private\ car} CD_i + \varepsilon_{Self-driving\ car,i} \quad (5)$$

$$U_{Driverless\ ridehailing,i} = V_{Driverless\ ridehailing,i} + \Gamma_{SP} SP_i + \Gamma_{CD,Driverless\ ridehailing} CD_i + \varepsilon_{Driverless\ ridehailing,i} \quad (6)$$

$V_{ji} = \beta X_{ji}$ is the deterministic part of the utility function for alternative j and decision-maker i. SP_i is the safety perception of individual i; CD_i is the car dependency of individual i. Γ_{SP} is estimated coefficient for safety perception; $\Gamma_{CD,private\ car}$ is estimated coefficient for car dependency for privately owned vehicles (e.g., regular car, and self-driving car); $\Gamma_{CD,\text{driverless ride-hailing}}$ is estimated coefficient for car dependency for driverless ride-hailing alternative. Results corresponding to different parts of the model are presented in Table 2, 3, and 4.

TABLE 2 ICLV model results

Variable		Estimate	Std error	*t*-test	*p*-value
Car					
Monthly Payment/Monthly Income		-3.08	0.41	-7.56	0.00
Parking fee/Daily Income		-6.60	2.84	-2.32	0.02
Travel Time (hr)	mean	-2.00	0.32	-6.29	0.00
	std. dev.	2.27	0.42	-5.41	0.00
ASC		0.98	0.27	3.63	0.00
Car dependency *(CD)*		1.22	0.14	8.53	0.00
Self-driving car					
Monthly Payment/Monthly Income		-3.08	0.41	-7.56	0.00

Parking fee/Daily Income		-6.60	2.84	-2.32	0.02
Travel Time (hr)	mean	-2.35	0.43	-5.49	0.00
	std. dev.	3.21	0.52	-6.22	0.00
ASC		0.16	0.28	0.55	0.58
Safety of AVs (*SP)*		0.46	0.04	12.30	0.00
Car dependency *(CD)*		1.22	0.14	8.53	0.00
Driverless Ride-hailing					
Cost/Daily Income		-5.21	0.69	-7.60	0.00
Wait Time (hr)		0.01	0.02	0.86	0.39
Travel Time (hr)	mean	-1.55	0.53	-2.95	0.00
	std. dev.	0.17	0.53	0.37	0.75
ASC		-0.83	0.30	-2.79	0.00
Safety of AVs *(SP)*		0.46	0.04	12.30	0.00
Car dependency *(CD)*		0.81	0.17	4.68	0.00
Ride-hailing					
Cost/Daily Income		-5.21	0.69	-7.60	0.00
Wait Time (hr)		0.01	0.02	0.86	0.39
Travel Time (hr)	mean	-4.42	0.89	-4.99	0.00
	std. dev.	2.44	0.68	3.60	0.00
ASC		0.16	0.28	0.58	0.56
Car dependency *(CD)*		0.57	0.17	3.34	0.00
Transit					
Cost/Daily Income		-5.21	0.69	-7.60	0.00
Wait Time (hr)		0.03	0.02	1.21	0.22
Travel Time (hr)	mean	-2.97	0.55	-5.42	0.00
	std. dev.	1.92	0.35	5.46	0.00
Bike					
Travel Time (hr)	mean	-10.80	1.28	-8.41	0.00
	std. dev.	-6.50	0.74	-8.82	0.00
ASC		2.63	0.29	8.93	0.00
Walk					
Travel Time (hr)	mean	-55.80	13.10	-4.26	0.00
	std. dev.	30.90	7.18	-4.31	0.00
ASC		5.08	0.59	8.58	0.00

Initial log likelihood: -18684.46
Final log likelihood: -13303.33
Adjusted Rho-square: 0.285
Akaike Information Criterion (AIC): 26708.66
Bayesian Information Criterion (BIC): 26944.49

We assumed a linear structural regression equation for the chosen latent variable. We created two age categories: Millennials and Generation Z (18-38 years old) and older respondents (39 years old and older). We included two income categories: over sample median (over $60,000) and under sample median (below $60,000). Table 3 shows the estimated structural model. We found that income is not statistically significant for neither safety perception nor car dependency. Individuals older than 38 years old perceive self-driving cars as less safe than younger individuals, and they are more car dependent. Also, individuals who identify themselves as males perceive self-driving cars as safer and are less car-dependent than their female counterparts.

TABLE 3 Structural model results

Structural Model	estimate	Std err	t-test	*p-value*
Safety Perception				
Age (Older than 38 years old)	-0.68	0.15	-5.01	0.00
Income (Over $60k)	-0.12	0.13	-0.95	0.34
Gender (Male)	0.84	0.13	6.47	0.00
Intercept	0.33	0.11	2.97	0.00
Error component	1.64	0.07	23.70	0.00
Car Dependency				
Age (Older than 38 years old)	0.17	0.07	2.41	0.01
Income (Over $60k)	0.09	0.07	1.32	0.19
Gender (Male)	-0.14	0.07	-2.16	0.03
Intercept	1.01	0.07	14.20	0.00
Error component	0.83	0.04	20.70	0.00

The measurement model links the latent variable to indicators. For the case of multinomial ordered with L responses (such as 6-point Likert scale, L = 6) we get:

$$I_i^* = Dx_i^* + \zeta_i \tag{7}$$

$$I_i = \begin{cases} 1 & if\ \gamma_0 < I_i^* < \gamma_1 \\ 2 & if\ \gamma_1 < I_i^* < \gamma_2 \\ & \vdots \\ L & if\ \gamma_{L-1} < I_i^* < \gamma_L \end{cases} \tag{8}$$

The first indicators' coefficient of both safety perception and car dependency were set to 1, and coefficients in other indicators are estimated relative to the first one. All the estimates have a positive value because higher-ranking responses correspond to a higher perception of self-driving car safety. Table 4 shows these estimates.

TABLE 4 Measurement model results

ID	Indicators	Estimates
Safety of AVS		
SP_1	I am ______ self-driving vehicles can drive as well as human drivers in general. (1- Extremely doubtful, 2- Doubtful, 3- A little doubtful, 4- Sort of confident, 5- Confident, 6- Extremely confident)	1.00
SP_2	Driverless cars generally will be ______compared with most drivers on the road. (1- Much more dangerous, 2- More dangerous, 3- Somewhat more dangerous, 4- A little safer, 5- Safer, 6- Much safer)	1.04
SP_3	Widespread use of self-driving vehicles would result in ______crashes. (1- A lot more, 2- More, 3- Slightly more, 4- Slightly fewer, 5- Fewer, 6- A lot fewer)	1.07
SP_4	Driverless cars generally will be ______than I am as a driver. (1- Much more dangerous, 2- More dangerous, 3- Somewhat more dangerous, 4- A little safer, 5- Safer, 6- Much safer)	0.90
SP_5	I ______trust self-driving car technology to keep me safe when I am riding in one. (1- Definitely would not, 2- Probably would not, 3- Maybe would not, 4- Maybe would, 5- Probably would, 6- Definitely would)	1.10
Car dependency		
CD_1	Owning a car is a(n) ______part of being an adult. (1- Not important at all, 2- Not important, 3- Not so important, 4- Somewhat important, 5- Very important, 6- Extremely important)	1.00
CD_2	Owning a car I can use anytime is ______. (1- Not at all important, 2- Not important, 3- Not so important, 4- Somewhat important, 5- Very important, 6- Extremely important)	1.83
CD_3	Driving my own car is ______ . (1- Not empowering at all, 2- Not empowering, 3- Not so empowering, 4- Somewhat empowering, 5- Very empowering, 6- Extremely empowering)	1.32
CD_4	The flexibility of driving by myself is ______. (1- Not at all important, 2- Not important, 3- Not so important, 4- Somewhat important, 5- Very important, 6- Extremely important)	1.65
CD_5	The ability to make spontaneous stops when I drive my own car is ______ to me. (1- Not at all important, 2- Not important, 3- Not so important, 4- Somewhat important, 5- Very important, 6- Extremely important)	1.40

The results show that perception of AVs safety and car dependency both have a direct, positive and statistically significant impact on the utility of self-driving cars and driverless ride-hailing service. The estimated magnitude of car dependency coefficient for privately owned options (regular car and self-driving car) is 1.6 times higher than driverless ride-hailing. This means that individuals who are more car dependent are more likely to choose privately owned car and self-driving car relative to driverless ride-hailing, and driverless ride-hailing over other modes (e.g. regular ride-hailing, transit, bike, and walk). Even though the in-vehicle experience in the driverless ride-hailing service and self-driving car is likely to be similar, larger psychological dependency on cars favors privately owned vehicles more than any other mode.

As individuals perceive AVs safer, they are more likely to choose them as their mode of transportation. We looked at the equivalent monetary weight of safety perception on the choice of self-driving cars and driverless ride-hailing services for an individual with a $60k income. A one unit improvement in the safety perception of self-driving cars or driverless ride-hailing, holding all else equal, increases the utility these modes by 0.46 units of utility.

$$\Delta\ utility = \beta_{Safety\ perception} . \Delta\ Safety\ perception \qquad (9)$$

$$\Delta\, utility = 0.46 \times 1$$

For the case of privately-owned self-driving car, this is similar to the change in utility that would result from decreasing the monthly car payment by about $750:

$$\Delta\, utility = \beta_{\frac{Monthly\ payment}{Monthly\ income}} . \Delta\, \frac{Monthly\ payment}{Monthly\ income} \tag{10}$$

$$0.46 = -3.08 . \frac{\Delta Monthly\ payment}{60{,}000/12} \rightarrow \Delta Monthly\ payment = -\$746.75$$

For driverless ride-hailing, a one unit improvement in safety perception provides the same utility benefit as decreasing cost of the trip by $14.53:

$$\Delta\, utility = \beta_{\frac{Ride\ cost}{Daily\ income}} . \Delta\, \frac{Ride\ cost}{Daily\ income} \tag{11}$$

$$0.46 = -5.21 . \frac{\Delta Ride\ cost}{60{,}000/365} \rightarrow \Delta Ride\ cost = -\$14.51$$

For both of the modes, the influence of a one unit change in safety perception is considerable. We explored four different scenarios, to demonstrate the potential impact of change in safety perception on the market share of driverless ride-hailing.

For the base scenario, we used attributes' base level and individuals' collected API data. The base level for self-driving car monthly payment and individuals who did not own a car was $500 and for individuals who owned a car we used their reported monthly payment.

For the first scenario, we decreased monthly cost of owning a self-driving car by 50% to $250. In the second scenario, we assumed that the cost of riding in a driverless ride-hailing service decreases by 75% due to eliminating labor costs. In the third scenario, we improved safety perception of some of the individuals by reducing the estimated safety perception distribution's variance. We achieved this distribution by reducing the difference between each person's fitted safety perception and the highest fitted safety perception value by half. Figure 6 shows expected responses to attitudinal statements when safety perception improves under this scenario and compares them with actual responses. Under scenario 3, everyone perceives AVs' safety positively.

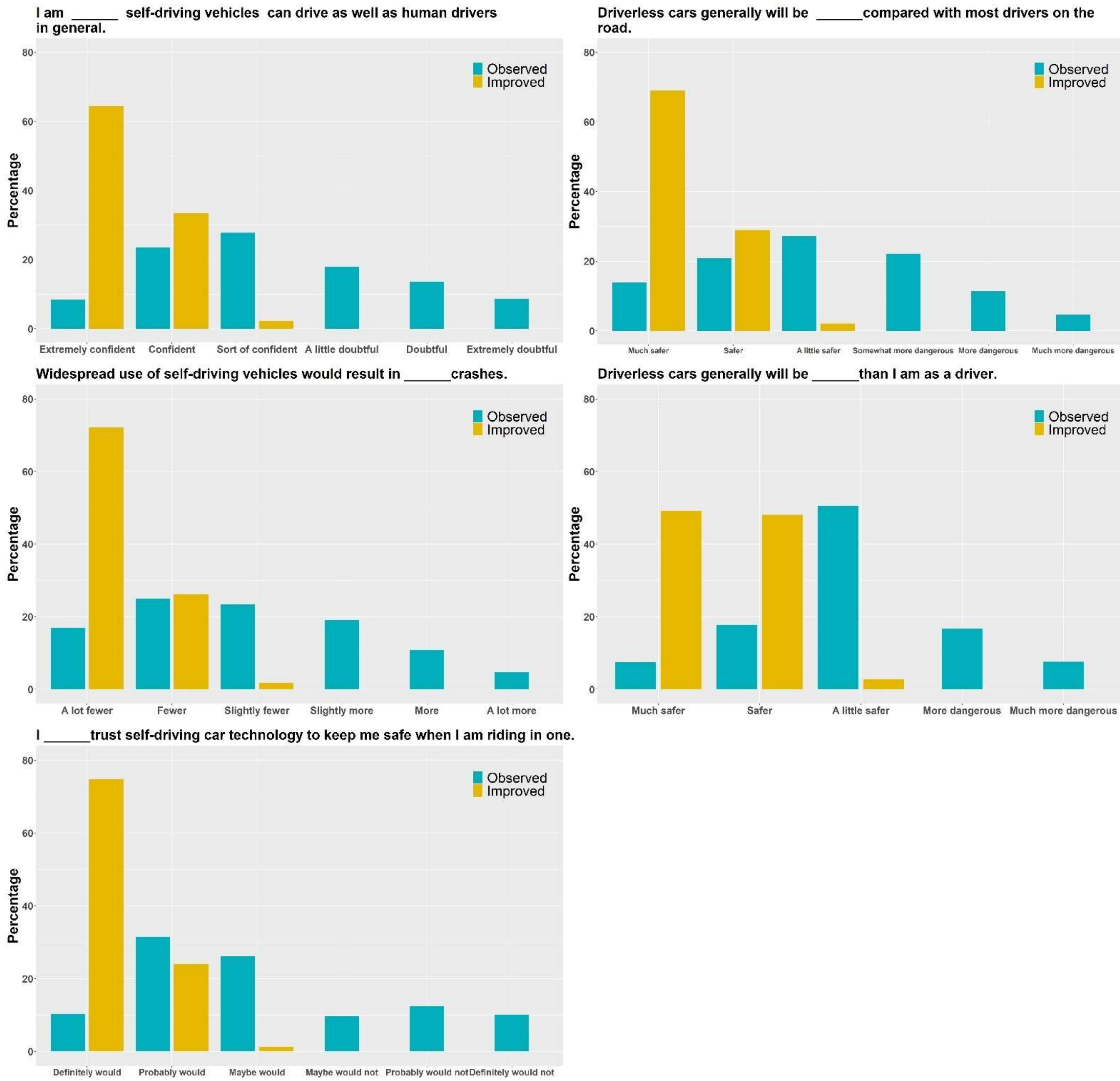

Figure 6 Expected responses after improved safety perception (scenario 3 and 4) vs observed responses

In the fourth scenario, we explored how simultaneous decrease in driverless ride-hailing cost and better safety perception affects the market share. Table 5 shows the market share of each mode under different scenarios.

TABLE 5 Market share under different scenarios

	Car	Self-driving car	Ride-hailing	Driverless ride-hailing	Transit	Bike	Walk
Base Scenario	68.6%	15.4%	0.1%	0.7%	1.4%	11.0%	2.6%
50% lower self-driving car price	65.1%	19.0%	0.1%	0.7%	1.4%	10.8%	2.6%
75% lower ride-hailing fares	63.0%	11.5%	0.1%	12.1%	0.9%	9.6%	2.5%
Improved Safety Perception	32.5%	50.8%	0.0%	3.6%	0.8%	9.5%	2.6%
Improved Safety Perception & 75% lower ride-hailing fares	29.7%	49.7%	0.0%	8.3%	0.5%	9.0%	2.6%

In scenario 1, market share of self-driving car increases by 3.6% due to halving the monthly payment while keeping the monthly payment for regular car the same as the base scenario. When cost of driverless ride-hailing drops to 25% of the current cost of ride-hailing services, driverless ride-hailing market share increases by 11.4%, mostly taking travelers from privately owned options. In scenario 3, when the perception of AVs safety improves, self-driving car dominates the market by taking approximately 50% of the market, and regular car's market share drops to less than half of its base scenario share. This scenario highlights the magnitude of safety perception effect on the market share. When safety perception improves, more people switch to AVs from their regular cars. In the last scenario, when we reduce driverless ride-hailing cost, self-driving car market share remains about the same relative to the third scenario, but market share of driverless ride-hailing doubles relative to the third scenario. In this scenario, driverless ride-hailing market share is still lower than the second scenario, even though both cost and safety perception have improved; This means that the overall utility of driverless ride-hailing does not overpass the utility of self-driving car.

These scenarios demonstrate that under current conditions, even AV prices were lower, we would not expect self-driving cars to take over private car market. They highlight the role safety perception can play on the demand for private AVs. As AVs' safety improve and consequently, the public's perception of safety improves, consumers will associate higher utility to self-driving cars and driverless ride-hailing services. Personal AVs' safety has the potential to compensate for their high costs. Consumers may be willing to pay more to use this technology if they perceive it as safe. For driverless ride-hailing, their mode share would grow if AVs allow a 75% reduction in fare, even if the safety perception remains the same as today. With safety perception improvements, more people would opt for privately owned self-driving cars, resulting in smaller mode share for driverless ride-hailing services.

CONCLUSION

Despite many potential merits counted for AVs, studies have found several barriers to AV adoption. The one obstacle that stands out the most during our literature review was the perception of safety. We were also interested in understanding challenges for the adoption of driverless ride-hailing service. We hypothesized that individuals who are psychologically attached to their car are more likely to avoid such a service.

In this paper, we quantified the impact of two latent constructs, public's safety perception and car dependency on choosing two AV options: 1) privately owned self-driving car and 2) driverless ride-hailing service. We used an integrated choice and latent variable model to model mode choice and incorporated the two latent variables through sets of structural and measurement equations.

We found that both safety perception and car dependency have a statistically significant effect on choosing AV modes. Our results show that car dependency has the most substantial impact on choosing privately owned cars, followed by driverless ride-hailing and regular ride-hailing. This finding confirms our initial hypothesis that the more psychologically attached individuals are to their vehicles, they are more likely to choose personal cars as their mode of transport. Interestingly, between the driverless ride-hailing and regular ride-hailing, individuals who are more car dependent prefer the former over the latter.

Another interesting finding of this analysis is the magnitude of safety perception effect on mode choice and how it compares with costs. We demonstrated how one unit change in safety perception means in terms of equivalent monetary impact. However, one unit of safety perception is not very intuitive. Therefore, we tested several scenarios to better grasp the effect of safety perception improvements. We determined a base scenario using API data collected for each individual's trip and base values for other attributes. Then, we discovered that shifting people's perceptions toward positive AV safety perception can drastically change AVs' market share. While keeping regular car monthly payments constant and reducing self-driving car payment, we observed that self-driving car market grew by 4.4%. However, when safety perception improved, its market share grew by about 35%, taking over 50% of the market. Based on our analysis, privately owned self-driving cars will dominate driverless ride-hailing services and reducing fare can help expand their market share.

Under current conditions, we would not expect self-driving cars to take over private car market. Even if prices were much cheaper, the market would only grow slightly. However, improving safety perception would have a big impact on demand for private AVs. In contrast, the mode share of driverless ride-hailing would grow substantially if AVs permitted a 75% reduction in fares, even if safety perceptions did not change from today. And if safety perceptions did improve, the effect for driverless ride-hailing could be negative, as more people would opt for personal AVs.

Moving forward, we think there is value in focusing on driverless ride-hailing and AV services in general and explore the potential latent constructs impacting their adoption. Also, it might be worthwhile to model self-driving car purchase decisions independently and investigate psychological constructs that influence purchase decisions.

ACKNOWLEDGMENTS

This project was funded by the US-China Clean Energy Research Center (CERC).

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: P. Jabbari, D. MacKenzie; data collection: P. Jabbari; analysis and interpretation of results: P. Jabbari, D. MacKenzie; draft manuscript preparation: P. Jabbari, D. MacKenzie. All authors reviewed the results and approved the final version of the manuscript.

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