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The effect of ride experience on changing opinions toward autonomous vehicle safety

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ABSTRACT

Autonomous vehicles (AVs) are a promising emerging technology that is likely to be widely deployed in the near future. People's perception on AV safety is critical to the pace and success of deploying the AV technology. Existing studies found that people's perceptions on emerging technologies might change as additional information was provided. To investigate this phenomenon in the AV technology context, this paper conducted real-world AV experiments and collected factors that may associate with people's initial opinions without any AV riding experience and opinion change after a successful AV ride. A number of ordered probit and binary probit models considering data heterogeneity were employed to estimate the impact of these factors on people's initial opinions and opinion change. The study found that people's initial opinions toward AV safety are significantly associated with people's age, personal income, monthly fuel cost, education experience, and previous AV experience. Further, the factors dominating people's opinion change after a successful AV ride include people's age, personal income, monthly fuel cost, daily commute time, driving alone indicator, willingness to pay for AV technology, and previous AV experience. These results provide important references for future implementations of the AV technology. Additionally, based on the inconsistent effects for variables across different models, suggestions for future transportation survey designs are provided.

1. Introduction

Autonomous vehicle (AV) technology holds the promise of bringing in tremendous benefits of safety, mobility, and energy efficiency to the near future traffic systems (Fraedrich et al., 2019; Li and Li, 2019; Naranjo et al., 2008; Shi and Li, 2019; Wang et al., 2019). Previous studies found that people's perceptions on traffic safety significantly influenced the acceptance of public transportation modes (Delbosc and Currie, 2012; Liljamo et al., 2018; Salonen, 2018). Studies in the UK suggested that about 10 percent of the population would change their opinion on using public transport if they thought the transportation mode was not safe (Concern, 2002). Empirical evidence from Norway and Milan, Italy, showed that traffic safety was the most important factor of public transport services (Eboli and Mazzulla, 2012; Masoumi and Fastenmeier, 2016). Especially, several fatal AV crashes in recent years due to the immature AV technology, e.g., the Uber AV collision in Arizona (2018) and the Tesla collision (Tesla, 2020), adversely impacted people's opinions toward the safety of the AV technology. To rebuild confidence in AV technology, on the one hand, it is essential to study the influence factors associated with people's initial opinions toward AV safety. On the other hand, how to effectively change people's initial opinions to be more positive toward AV safety need to be investigated.

Studies investigating factors correlated to AV acceptance were abundant in the literature (Bansal and Kockelman, 2017; Jing et al., 2020; Lavasani et al., 2016; Nordhoff et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Xu et al., 2018). However, studies specifically focusing on factors affecting people's opinion on AV safety were relatively scarce. Wang and Zhao (2019) studied the risk preference of AV by using a stated preference survey data collected in Singapore. The results indicated that the elderly, poor, female, and unemployed respondents were more risk-averse and thus were less likely to adopt AVs. Besides the factors mentioned by Wang and Zhao (2019), Sheela and Mannering (2019) found that the injury experience was also related to people's opinions on AV safety by using the survey data collected in the United States. Cunningham et al. (2019) revealed that even respondents in Australia intended to agree with many of the potential benefits, such as

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the predicted safety of AV, a majority of them were not willing to pay any more for the AV technology. Salonen (2018) suggested that AVs are safer than conventional buses, but less in-vehicle security and emergency management regarding the survey in Finland. Despite these successful studies, most existing studies did not analyze the impact of AV riding experience, and in particular, the change of opinion before and after a successful AV ride. Without this knowledge, it is not clear how to design and implement proper interventions such as inviting people to ride AVs to effectively improve people's confidence on AV safety.

However, many studies investigated factors making people more or less likely to change their opinions as additional information is gathered in other application contexts (Chandrashekaran and Grewal, 2006; Smith et al., 2013; Verousis and Ap Gwilym, 2014). Tversky and Kahneman (1974) referred to this as an anchoring effect, where opinions are biased towards initially gathered values. The variety of the anchoring effect was studied in many fields. For example, Adomavicius et al. (2013) studied the anchoring effect of recommender systems in e-commerce websites. They explored how consumer preferences at the time of consumption were impacted by the predictions generated by recommender systems. Bowman and Bastedo (2011) investigated the anchoring effects in world university rankings, and they found that the initial rankings of a new ranking system influenced peer assessments of reputation in subsequent surveys.

A successful AV ride experience undoubtedly provides people with positive information that may change their opinions on safety, which has been verified by a series of AV pilots (City of Las Vegas, 2020; Mahmoodi Nesheli et al., 2021; Morra et al., 2019; Salonen, 2018). For example, the Milo Pilot project (City of Arlington, 2018) conducted at Arlington, Texas, United States, found that after a successful AV ride, 99% of riders felt safe, and 97% of them supported AV technology more broadly. The CityMobil2 project (Portouli et al., 2018) conducted at Trikala, Greece, found that participants who rode on the AV shuttle developed a more positive attitude towards AVs. The MnDOT autonomous bus pilot project (Borgen and Taavola, 2018) demonstrated at Minnesota, United States, revealed that after riding the AV, 96.4% of respondents had a positive attitude towards AV safety. However, the existing AV pilot reports only conducted simple analyses to the survey data, while most of the reports did not include the demographic data, which impedes further investigating this effect on different popultation groups. Further, none of these studies investigated the anchoring effect of a successful AV ride experience on changing opinions toward AV safety.

The most related studies to this paper were Eden et al. (2017) and Sheela and Mannering (2019) that however focused on AV acceptance instead of AV safety. Eden et al. (2017) conducted a pilot study using AVs to transport people on a specified route. People's opinions and attitudes both before and after riding were asked to study the influence of an actual experience toward AV acceptance. However, the number of samples in their study was quite limited, only including 13 passengers. Sheela and Mannering (2019) focused on how people's initial AV adoption likelihoods change after being asked a common set of questions that lead them through an assessment of factors involved in adoption. They adopted statistical models to study the opinion data, and the results indicated that people's opinions on AV adoption before and after being given additional information should be estimated by separate models, demonstrating the existence of the anchoring effects in AV technology and further motivating the investigation of this paper.

Overall, this paper aims to fill the proposed research gap by studying the factors that are associated with people's initial opinions and opinion change toward the safety of AVs when a successful AV ride experience is provided. The contributions of this paper are threefold. Firstly, this paper collected the people's opinion data regarding the safety of AV technology before and after providing a successful real-world AV ride. Secondly, a series of discrete outcome models considering heterogeneity in the data was proposed to study the factors influencing people's initial opinions and opinion change. Thirdly, the results obtained by this paper provide managerial and regulatory insights into the future implementations of AV technology to the operators and policymakers.

The rest of this paper is organized as follows. Section 2 presents the opinion data and methodological approaches in detail. Section 3 shows the model estimation results for people's initial opinions and opinion change toward AV safety. Based on the obtained results, Section 4 concludes the paper and provides a discussion of the directions for future research.

2. Methods

2.1. Data

The opinion data used in this study are from the survey data collected during an AV demonstration at the 2019 Florida Automated Vehicles (FAV) Summit. Fig. 1 shows the AV used in this demonstration developed by the Connected and Autonomous Transportation System (CATS) lab at the University of South Florida. Fig. 2 shows the settings of the AV ride, and the overall length of the path is around 200 m. Participants firstly filled the before-the-ride questions in the questionnaire and waited at location A for the ride. In each ride, 1 to 4 people in the queue were served, and the AV automatically drove the participants from location B to location C along the route shown as the blue curve in Fig. 2. Each group of people took two rides, one for AV control alone, the other for AV control in conjunction with communications with a portable signal light utilizing the connected vehicle technology. After the AV rides, participants filled the after-the-ride questions and returned the questionnaires to the recorders.

In the end, data from a total of 166 participants were obtained. All participants indicated that they commuted to work or school. Compared with the United States population as a whole, participants of the summit had a higher level of understanding of the AV technology and a higher annual personal income, simply because the participants were from the conference attendees that apparently received better educations and more exposure to transportation. Despite the biased samples, these participants randomly distribute across the whole population and would be likely among the first group of people who adopt or accept AV technologies. Thus, it remains meaningful and informative to study the opinions of them toward AV safety.

The survey data contain three categories of information in general: 1) basic information about the participants (including demographics of the participants, daily commute information, and previous experience on emerging vehicle technologies, etc.), 2) opinions toward the safety of the AV technology before taking the AV ride, and 3) opinions toward the safety of the AV technology after taking the AV ride. Participants provided a 5-point scale ranging from strongly disagree, disagree, neutral, agree, strongly agree to indicate their opinions. The detailed questionnaire form used for collecting the data is provided in the Appendix. Note that by checking the collected data, no strongly disagree opinions are found in both before and after having the AV ride, and the frequencies of

Fig. 1. Test AV developed by the CATS lab at the University of South Florida.

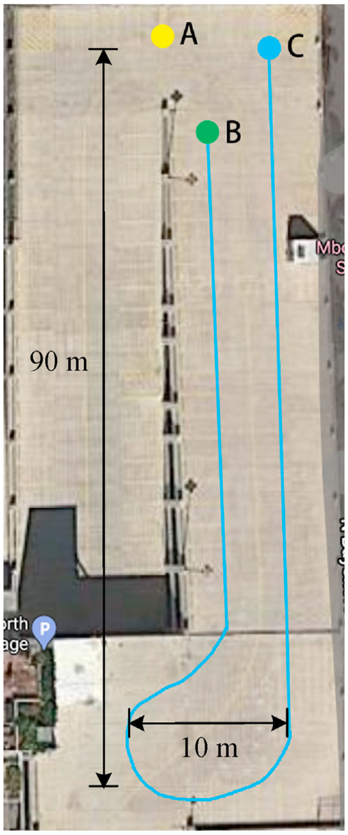

Fig. 2. Test site of the AV ride (Source: Google maps).

opinions for before and after the AV ride are shown in Table 1, respectively. As a result, only four opinion categories toward the safety of the AV technology (i.e., "disagree", "neutral", "agree", "strongly agree") are studied in this paper.

2.2. Methodological approach – initial opinion

The participants' initial opinions on AV safety are studied first. It is essential since the initial opinions may cause the anchoring effects that will affect the participants' final opinions (Sheela and Mannering, 2019). Due to the ordinality of the responses to AV safety, an ordered probability modeling approach is adopted for the analysis (Washington et al., 2011). Traditional ordered probability models are specified by defining an unobserved variable, z, for each observation n as the linear function,

$$z_n = \beta X_n + \varepsilon_n, \tag{1}$$

where X_n is a vector of explanatory variables determining the discrete answers for participant i, β is a vector of estimable parameters, and ε_n is a disturbance term. Note that in the estimation, the non-numerical ordered initial opinions, y_n^B (B represents before the AV ride), are converted to integers without loss of generality (i.e., 1 = "disagree", 2 = "neutral", 3 = "agree", 4 = "strongly agree"),

Table 1
Frequencies of AV safety opinions for both before and after the AV ride.

Opinion	Before the AV ride	After the AV ride
Disagree	13	7
Neural	81	28
Agree	50	79
Strongly agree	22	52

$$\begin{cases} y_n^B = 1 & z_n \le \mu_0\,, \\ y_n^B = 2 & \mu_0 \le z_n \le \mu_1, \\ y_n^B = 3 & \mu_1 \le z_n \le \mu_2, \\ y_n^B = 4 & z_n > \mu_2\,, \end{cases} \tag{2}$$

where μ's are estimable parameters (thresholds) that define y_n^B and are estimated jointly with the model parameters β. With this, if ε_n is assumed to be normally distributed across observations with mean equal to 0 and variance equal to 1, the ordered selection probability is

$$\begin{cases} P(y^B = 1) = \Phi(-\beta X), \\ P(y^B = 2) = \Phi(\mu_1 - \beta X) - \Phi(-\beta X), \\ P(y^B = 3) = \Phi(\mu_2 - \beta X) - \Phi(\mu_1 - \beta X), \\ P(y^B = 4) = 1 - \Phi(\mu_2 - \beta X), \end{cases} \tag{3}$$

where $\Phi(\cdot)$ is the standardized cumulative normal distribution.

To capture unobserved heterogeneity, the random parameters approach (Washington et al., 2011) is integrated into the model, and thus the parameters can vary across observations. The estimable parameters are written as,

$$\beta_n = \beta + w_n, \tag{4}$$

where β_n is a vector of estimable parameters that potentially varies across observations n, β is the vector of mean parameter estimates across all observations, and w_n is a vector of randomly distributed terms (e.g., normally distributed term with mean zero and variance σ^2). Estimation of the random parameters ordered probit is undertaken by the simulated maximum likelihood approach. It was found that Halton draws yields a more efficient distribution of simulation draws than purely random draws (Bhat, 2003). Thus, the model estimations of this paper adopt 1000 Halton draws in the simulated likelihood functions, a number that has been shown to be more than sufficient to provide accurate parameter estimates (Alnawmasi and Mannering, 2019).

2.3. Methodological approach – opinion change

As discussed earlier, due to the anchoring effects, initial opinions are likely to be the critical determinants of final opinions and thus serve as a guide to any change in these opinions. To establish that participants' opinions were not stable between their initial assessment of AV safety and their final assessment (after having the AV ride), estimation results from three ordered probit models are used: an initial model (opinions before the AV ride estimated as shown in Table 2), a final model (opinions after having the AV ride), and an overall model that includes opinions both before and after the AV ride. With these model estimates, a likelihood ratio test was conducted as $\chi^2 = -2[LL(\beta)_{combined} - LL(\beta)_{before} - LL(\beta)_{after}]$, where $LL(\beta)_{combined}$ is the log-likelihood at the convergence of a model using the data from both before and after providing the AV ride, $LL(\beta)_{before}$ is the log-likelihood at the convergence of a model estimated before providing the AV ride, and $LL(\beta)_{after}$ is the log-likelihood at convergence of a model after providing the AV ride. The resulting χ^2 statistic (with the degrees of freedom equal to the summation of the number of parameters in the before and after models minus the number of estimated parameters in the combined model) is 58.44, and the degrees of freedom are 8. This χ^2 value suggests that there is more than 99% confidence that the before and after parameter values are not the same, suggesting that the AV ride experience significantly affects individual opinions on AV safety.

With this result, a series of models are estimated to understand which factors determine the likelihood of participants shifting from their initial opinions about AV safety. The ordered probit estimation results provide insights into the factors that influence the initial opinions on AV safety. Here we focus on opinion change from different initial opinions,

Table 2
Random parameter ordered probit model of the initial opinions toward the safety of the av technology [dependent variable responses are integers between 1 (disagree) to 4 (strongly agree)].

Variable Description	Estimated Parameter	*t* Statistic
Constant (standard deviation of parameter distribution)	1.918 (0.612)	7.36 (5.88)
High income indicator (1 if participant's annual personal income is greater than $150,000, 0 otherwise) (standard deviation of parameter distribution)	−0.598 (0.670)	−2.20 (2.84)
Age indicator (1 if participant's age is greater than 30 years old) (standard deviation of parameter distribution)	0.710 (0.791)	2.86 (6.56)
High education indicator (1 if participant holds a master's degree or above, 0 otherwise)	−0.836	−4.15
Auto Pilot ride experience indicator (1 if participant ever had Auto Pilot ride experience, 0 otherwise)	0.729	3.43
High monthly fuel cost indicator (1 if participant's monthly fuel cost is greater than $200, 0 otherwise)	−0.604	−1.94
Threshold 1	2.291	9.83
Threshold 2	3.915	12.55
Number of observations	161	
Log-likelihood at convergence	−174.465	
Log-likelihood at constant	−190.304	

including “disagree”, “neutral”, “agree”, and “strongly agree”.

However, due to the limited number of observations, only 13 and 22 participants' initial opinions are in the “disagree” and “strongly agree” categories, respectively. Continuously using the statistical models to estimate the influence factors for these two categories may lose significance. Therefore, only the opinion change of the participants whose initial opinions are “neutral” and “agree” are studied in the rest of this paper. Also, this paper is especially interested in the factors that can enhance participants’ opinions about AV safety. To facilitate the analysis, the after-the-ride opinions are reclassified into two categories, including non-positive (negative or unvaried opinions) and positive opinions. For example, for participants whose initial opinions are neutral, the after-the-ride option of “disagree” is categorized as non-positive, that of “neutral” as non-positive, and that of “agree” or “strongly agree” as positive. Due to the characteristics of the responses (either non-positive or positive), a set of binary probit models are developed as well to determine the probabilities for a participant to change opinions. The model formulation of the binary probit model is as follows. The after-the-ride opinions, y_n^A (A represents after having the AV ride experience), are converted to binary integers as 1 for non-positive, 2 for positive. The definitions of the symbols are the same as we defined previously.

$$\begin{cases} P\left(y^A = 1\right) = \Phi((\beta_1 X_1 - \beta_2 X_2)/\sigma), \\ P\left(y^A = 2\right) = 1 - \Phi\left(y^A = 1\right). \end{cases} \tag{6}$$

Also, to allow for random parameters in this binary probit model, the estimable parameters are written as,

$$\beta_n = \beta + w_n. \tag{7}$$

3. Estimation results

3.1. Initial opinion estimation and results

The estimation results of the random parameter ordered probit model for the initial opinions toward the safety of the AV technology are shown in Table 2, and the corresponding marginal effects are shown in Table 3. It can be seen in Table 2 that five variables are found to significantly affecting participants’ initial opinions on AV safety. Among these variables, the high-income indicator variable and the age indicator variable are found to produce normally distributed random parameters with

Table 3
Average marginal effects for the initial opinions toward AV safety model.

Variable Description	Marginal Effects			
	Disagree	Neutral	Agree	Strongly Agree
High income indicator (1 if participant's annual personal income is greater than $150,000, 0 otherwise)	0.0371	0.1768	−0.1778	−0.0361
Age indicator (1 if participant's age is greater than 30 years old)	−0.0449	−0.2077	0.2091	0.0435
High education indicator (1 if participant holds a master's degree or above, 0 otherwise)	0.2813	−0.2398	−0.0767	0.0352
Auto Pilot ride experience indicator (1 if participant ever had Auto Pilot ride experience, 0 otherwise)	−0.0269	−0.2536	0.2085	0.0719
High monthly fuel cost indicator (1 if participant's monthly fuel cost is greater than $200, 0 otherwise)	0.0390	0.1752	−0.1791	−0.0351

statistically significant standard deviations, which indicates significant unobserved heterogeneity across the participants. The high-income indicator variable is used to describe participants whose annual personal income is greater than $150,000. Its estimated mean parameter and standard deviation are −0.598 and 0.670, respectively, which indicates that the effect of this variable increases the likelihood of having a neutral opinion on AV safety by roughly 74.0%. The age indicator variable is used to describe participants whose age is greater than 30 years old. Its estimated mean parameter and standard deviation are 0.710 and 0.791, respectively, which indicates that the effect of this variable increases the likelihood of having an “agree” opinion on AV safety by roughly 53.5%.

For other statistically significant variables, participants who hold a master's degree or above and whose monthly fuel costs are greater than $200 have lower probabilities of having “agree” or “strongly agree” opinions on AV safety. For the high education participants' result, we can interpret it as that the researchers may not likely express their opinions without strong evidence. In addition, we would like to mention that the AV pilot conducted at Lausanne, Switzerland (Vollichard, 2018) found that respondents with and without Bachelors' degrees reported similar acceptance of AV, which indicates that the education background does not much impact people's opinions on AV technology. These contrary results open up future research needs for investigating education background on AV technology, especially when the respondents are from different countries. Further, a high monthly fuel cost probably indicates that the participants spent a long commute time, which was likely associated with adversary driving/riding experience such as excessive congestion and stop-and-go traffic. Such adversary experience might deteriorate their confidence in AV safety.

On the contrary, participants who owned Auto Pilot ride experience have higher probabilities of agreeing or strongly agreeing on the safety of the AV. This result is consistent with the previous studies (Becker and Axhausen, 2017) and our expectation that successful AV rides positively impacts people's opinions toward AV safety.

3.2. Opinion change estimation and results

The binary probit models with random parameters are used to estimate participants' opinion change after a successful AV ride. The model estimation results of opinion change (conditioning on participants’ initial opinions) are presented in Tables 4–7. Detailed model results are discussed in each subsection below.

3.2.1. Participants with an initial opinion of neutral

Due to incomplete data issues, 76 out of 81 participants whose initial

Table 4
Opinion change model for participants with an initial AV safety opinion on the "neutral".

Variable Description	Estimated Parameter	*t* Statistic	Marginal Effects
Constant (standard deviation of parameter distribution)	3.929 (0.854)	2.74 (3.06)	
Long commute time indicator (1 if participant's commute time is greater than 20 min, 0 otherwise) (standard deviation of parameter distribution)	−0.374 (1.339)	−0.65 (2.81)	−0.038
Participant's age	−0.104	−3.08	−0.010
Participant's annual personal income in thousand dollars	0.021	2.36	0.002
Drive alone indicator (1 if participant drives alone to commute, 0 otherwise)	−1.910	−1.69	−0.192
Participant's monthly fuel cost in dollars	0.010	2.09	0.001
Adaptive cruise control ride experience indicator (1 if participant ever had adaptive cruise control experience, 0 otherwise)	1.129	1.86	0.113
Number of observations	76		
Log-likelihood at convergence	−31.954		
Log-likelihood at constant	−39.114		

Table 5
Factors increasing/decreasing the likelihood of opinion change with an initial AV safety opinion on the "neutral".

Factors increasing the likelihood of an opinion change
Participant's annual personal income in thousand dollars
Participant's monthly fuel cost in dollars
Adaptive cruise control experience indicator (1 if participant ever had adaptive cruise control ride experience, 0 otherwise)
Factors decreasing the likelihood of an opinion change
Long commute time indicator (1 if participant's commute time is greater than 20 min, 0 otherwise)
Participant's age
Drive alone indicator (1 if participant drives alone to commute, 0 otherwise)

Table 6
Opinion change model for participants with an initial AV safety opinion on the "agree".

Variable Description	Estimated Parameter	*t* Statistic	Marginal Effects
Constant	−10.988	−1.69	
High-income indicator (1 if participant's annual personal income is greater than $150,000, 0 otherwise)	3.895	1.57	0.307
Participant's daily commute time in minutes	0.244	1.68	0.019
Participant's monthly fuel cost in dollars	0.033	1.77	0.003
Adaptive cruise control ride experience indicator (1 if participant ever had adaptive cruise control experience, 0 otherwise)	−2.326	−1.46	−0.149
High technical package cost indicator (1 if participant's willing-to-pay for technical packages is over $3,000, 0 otherwise)	−1.751	−1.63	−0.160
Number of observations	46		
Log-likelihood at convergence	−6.420		
Log-likelihood at constant	−30.789		

opinions on AV safety are "neutral" are used to estimate the opinion change model. Roughly 84.2% of participants changed their opinions on AV safety after the provided AV ride (3.1% to "disagree", 72.3% to "agree", 24.6% to "strongly agree"). For model estimation simplification, the opinions after the AV ride are reassigned into two categories, such as non-negative (i.e., "disagree" and "neutral") and positive (i.e., "agree" and "strongly agree"). The estimation results and the corresponding marginal effects are shown in Table 4. For readers' convenience, Table 5 lists the factors increasing/decreasing the likelihood of a positive opinion change with an initial AV safety opinion of being "neutral".

Table 7
Factors increasing/decreasing the likelihood of opinion change with an initial AV safety opinion on the "agree".

Factors increasing the likelihood of an opinion change
High-income indicator (1 if participant's annual personal income is greater than $150,000, 0 otherwise)
Participant's daily commute time in minutes
Participant's monthly fuel cost in dollars
Factors decreasing the likelihood of an opinion change
Adaptive cruise control ride experience indicator (1 if participant ever had adaptive cruise control experience, 0 otherwise)
High technical package cost indicator (1 if participant's willing-to-pay for technical packages is over $3,000, 0 otherwise)

It can be seen that in Table 4, six variables are found to significantly affect participants' opinion change on AV safety, among which the long commute time indicator variable is found to produce normally distributed random parameters with statistically significant standard deviations. The long commute time indicator variable is used to describe participants whose daily commute time is greater than 20 min, and the estimated mean parameter and standard deviation for it are −0.374 and 1.339, respectively. It is found that if the participant's commute time is greater than 20 min, the possibility for this participant to positively change his/her opinion of being "neutral" will be decreased. Together with the results of the initial opinion model that the high fuel cost participants have low probabilities of having "agree" or "strongly agree" opinions on AV safety, we can infer that participants with long travel time and distance have higher probabilities of having negative opinions on AV safety even after being provided the AV ride, and their opinions are less likely to be shifted. As aforementioned, this may be because the existing AV technology cannot satisfy their daily travel requirements. Moreover, we would like to point out that even we found that the long commute time indicator variable is with normally distributed random parameters, which provide informative insights into the participants' opinions. However, due to the sparse sample size, this finding needs to be further verified.

For other statistically significant variables shown in Tables 4 and 5, participant's annual personal income, participant's monthly fuel cost, and adaptive cruise control experience indicator increase the likelihood of a positive opinion change with an initial AV safety opinion of being "neutral". Note that the high-income indicator variable in the initial opinion model increases the likelihood of having the "neutral" opinion on AV safety by roughly 74.0%. However, after having a successful AV ride, the results indicate that high-income participants change their opinions from "neutral" to "agree" or "strongly agree", which demonstrates the significances of a successful AV ride experience on high-income participants' opinions toward AV safety. On the contrary, participants who drive alone to commute have a lower likelihood of opinion change with an initial "neutral" opinion.

3.2.2. Participants with an initial opinion of agree

Also, due to incomplete data issues, 46 out of 50 participants with an initial "agree" opinions are used to estimate the opinion change model. Roughly 54.3% of participants changed their opinions on AV safety after the provided AV ride (7.7% to "disagree", 19.2% to "neutral", 73.1% to "strongly agree"). This opinion changing pattern is similar to that of the previous model for an initial "neutral" opinion. The new model for an initial "agree" opinion reassigns people's opinion change into two categories, including non-positive (i.e., "disagree", "neutral" and "agree"), and positive (i.e., “strongly agree”). The estimation results of this model and the corresponding marginal effects are shown in Table 6. For readers' convenience, Table 7 lists the factors increasing/decreasing the likelihood of opinion change with an initial “agree” opinion. It can be seen that in Table 6, five variables are found to significantly affect participants' opinion change on AV safety, but none of them is found owning significant unobserved heterogeneity. It is found that if the participant's annual personal income is greater than $150,000, the possibility for this participant to positively change his/her opinion toward AV safety after the AV ride will be increased. Together with the previous model results, we find that the AV ride experience on high-income participants' opinion change is significant. That is, in the initial opinion model, we find that the high-income indicator variable increases the likelihood of participants' initial “neutral” opinion. However, after the AV ride, this variable shows significant positive effects on improving participants' opinions toward AV safety (i.e., from neutral to agree or strongly agree, and from “agree” to “strongly agree”) based on their initial opinions. This finding suggests that demonstration rides may be targeted at the high-income population to get good outcomes in improving the population's confidence in AV safety.

For other statistically significant variables, as shown in Tables 6 and 7, participant's daily commute time, and participant's monthly fuel cost increase the likelihood of a positive opinion change with an initial “agree” opinion. Note that the higher values of participant's daily commute time and higher participant's monthly fuel costs indicate longer travel distances (or times). However, the effects of these variables on the opinion change models for the “neutral” and “agree” initial opinions are inconsistent. Participants with longer travel distances (or higher fuel costs) and the initial “neutral” opinion tend to keep the same opinion even after the AV rider. Whereas participants with longer travel distances (or higher fuel costs) yet the initial “agree” opinion tends to change positively. This indicates that an initial “agree” opinion may be further enhanced by the AV riding experience for certain population groups, and these people could be the primary target for promoting AV technology safety.

However, participants who had the adaptive cruise control ride experience have a lower likelihood of a positive opinion change with an initial “agree” safety opinion. This could be possible because that the adaptive cruise control system of current commercial vehicles is only dependent on radar sensors. The adaptive cruise control performance may not always meet users' high expectations (Shi and Li, 2021), which might render the users more conservative on AV safety. In addition, the high cost for the technical packages of the AV also decreases the likelihood of a positive opinion change with an initial “agree” opinion, which is consistent with the previous studies' finding that additional cost on AV technical package will degrade people's interests on AV (Bansal and Kockelman, 2017; Cunningham et al., 2019; Kyriakidis et al., 2015). This finding implicates that to implement AV technology, it is crucial to balance AV cost and performance.

3.3. Summary of findings

Table 8 presents a summary of all significant variables found at least in one of the initial opinions and opinion change models.

We can observe that although participants with higher annual personal incomes intend to be conservative on AV safety, their opinions may be significantly changed toward the positive side after a successful AV ride, based on the results of variables participant's annual personal income and high-income indicator. Thus, the high-income people could be the ideal customer group for promoting AV technology safety using AV riding demonstrations.

It is also seen that variable participant's monthly fuel cost's effects on participants' opinions after the AV ride are consistent across the two opinion change models. It increases the likelihood of opinion change towards the positive side. This finding also helps identify another group of customers whose opinions may be relatively easily shifted towards the positive side with a successful AV riding experience.

The other variables may be significant in only one of the models. The inconsistency of these results is also an important finding. As discussed by Sheela and Mannering (2019), the anchoring effects caused by the successful AV ride may not be consistently explained by traditionally collected variables. To understand the deeper reasons leading to the inconsistency, additional variables, such as behavioral and psychological variables, may need to be further collected. This finding provides important implications for the future transportation survey design, especially when studying emerging technologies, such as AV technology, clean energy vehicles, and wireless charging vehicle technology, etc.

Table 8
Summary of initial opinion and opinion change models findings.

Variable Description	Initial opinion model	Opinion change model	
		Neutral	Agree
Adaptive cruise control experience indicator (1 if participant ever had adaptive cruise control ride experience, 0 otherwise)	n	+	−
Age indicator (1 if participant's age is greater than 30 years old)	+	n	n
Auto Pilot ride experience indicator (1 if participant ever had Auto Pilot ride experience, 0 otherwise)	+	n	n
Drive alone indicator (1 if participant drives alone to commute, 0 otherwise)	n	−	n
High technical package cost indicator (1 if participant's willing-to-pay for technical packages is over $3,000, 0 otherwise)	n	n	−
High income indicator (1 if participant's annual personal income is greater than $150,000, 0 otherwise)	−	n	+
High monthly fuel cost indicator (1 if participant's monthly fuel cost is greater than $200, 0 otherwise)	−	n	n
High education indicator (1 if participant holds a master's degree or above, 0 otherwise)	−	n	n
Long commute time indicator (1 if participant's commute time is greater than 20 min, 0 otherwise)	n	−	n
Participant's age	n	−	n
Participant's annual personal income in thousand dollars	n	+	n
Participant's monthly fuel cost in dollars	n	+	+
Participant's daily commute time in minutes	n	n	+

Note: In the initial opinion model, “+” indicates the variable with a positive effect on the initial opinion, “-” with a negative effect on the initial opinion; In the opinion change model, “+” indicates the variable contributing to positive opinion change, “-” maintaining the same opinion or worse; “n” indicates no significant effects.

4. Discussion and conclusions

AV technology arguably is one of the most promising technologies in the near future. Understanding factors that affect the potential consumers’ opinions toward AV safety are crucial to building confidence in the AV technology and thus facilitating the future deployment of the technology.

This paper focuses on studying the anchoring effects caused by a successful AV ride experience on people's opinions toward AV safety. Specifically, a series of discrete statistical models considering heterogeneity in the data are employed to estimate the factors that are associated with people's initial opinions and opinion change toward AV safety after being provided a successful AV ride. Explanatory variables significantly affected people's initial opinion and opinion change are found by the estimation results of the proposed models, respectively. Based on the result analysis, this paper finds that 1) participants with higher annual personal incomes intend to be conservative on AV safety, their opinions may be significantly changed toward the positive side after a successful AV ride; 2) participants with higher monthly fuel cost may be relatively easily shifted towards the positive side with successful AV riding experience. These findings provide managerial insights into policy making of AV technology demonstration and promotion. Further, the inconsistency of the anchoring effects provides important implications for future transportation survey design.

This study was constrained by several limitations. First, it was mentioned in the paper that due to the insufficient data issue, the opinion change models only studied the participants whose initial opinions were “neutral” and “agree”. Therefore, one future direction is to enrich the dataset and investigate all possibilities for opinion change. Second, due to the uncertainties and evolutions of AV technology, people's opinions toward AV safety may change as well and thus the findings in this paper can only represent people's opinions toward current AV technology. Third, safety is not the only concern of people for AV technology. It is also interesting to investigate people's opinions on other concerns, such as comfort, time saving, fuel saving, in-vehicle safety, etc. Moreover, we provided AV rides with a given path and speed profile. It will be interesting to study the relationship between the performance of the AV in the test ride (e.g., driving aggressiveness) and the changes of safety perception.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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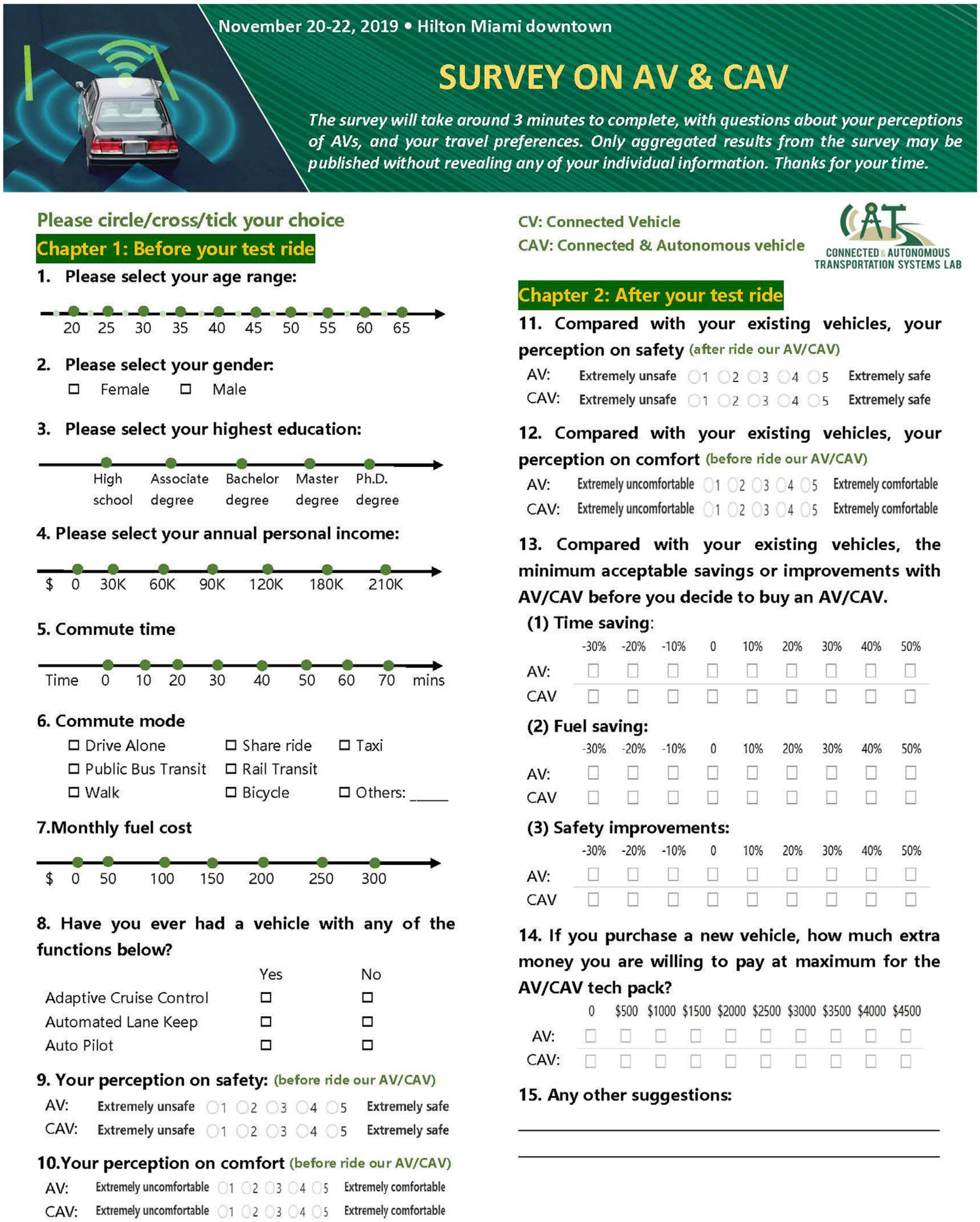
Appendix A. Questionnaire form



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SURVEY ON AV & CAV

The survey will take around 3 minutes to complete, with questions about your perceptions of AVs, and your travel preferences. Only aggregated results from the survey may be published without revealing any of your individual information. Thanks for your time.

Please circle/cross/tick your choice

CV: Connected Vehicle
CAV: Connected & Autonomous vehicle

CONNECTED & AUTONOMOUS TRANSPORTATION SYSTEMS LAB

Chapter 1: Before your test ride

1. Please select your age range:
20 25 30 35 40 45 50 55 60 65

2. Please select your gender:
☐ Female ☐ Male

3. Please select your highest education:
High school | Associate degree | Bachelor degree | Master degree | Ph.D. degree

4. Please select your annual personal income:
$ 0 30K 60K 90K 120K 180K 210K

5. Commute time
Time 0 10 20 30 40 50 60 70 mins

6. Commute mode
☐ Drive Alone ☐ Share ride ☐ Taxi
☐ Public Bus Transit ☐ Rail Transit
☐ Walk ☐ Bicycle ☐ Others: _____

7. Monthly fuel cost
$ 0 50 100 150 200 250 300

8. Have you ever had a vehicle with any of the functions below?

	Yes	No
Adaptive Cruise Control	☐	☐
Automated Lane Keep	☐	☐
Auto Pilot	☐	☐

9. Your perception on safety: (before ride our AV/CAV)
AV: Extremely unsafe ○1 ○2 ○3 ○4 ○5 Extremely safe
CAV: Extremely unsafe ○1 ○2 ○3 ○4 ○5 Extremely safe

10. Your perception on comfort (before ride our AV/CAV)
AV: Extremely uncomfortable ○1 ○2 ○3 ○4 ○5 Extremely comfortable
CAV: Extremely uncomfortable ○1 ○2 ○3 ○4 ○5 Extremely comfortable

Chapter 2: After your test ride

11. Compared with your existing vehicles, your perception on safety (after ride our AV/CAV)
AV: Extremely unsafe ○1 ○2 ○3 ○4 ○5 Extremely safe
CAV: Extremely unsafe ○1 ○2 ○3 ○4 ○5 Extremely safe

12. Compared with your existing vehicles, your perception on comfort (before ride our AV/CAV)
AV: Extremely uncomfortable ○1 ○2 ○3 ○4 ○5 Extremely comfortable
CAV: Extremely uncomfortable ○1 ○2 ○3 ○4 ○5 Extremely comfortable

13. Compared with your existing vehicles, the minimum acceptable savings or improvements with AV/CAV before you decide to buy an AV/CAV.

(1) Time saving:

	-30%	-20%	-10%	0	10%	20%	30%	40%	50%
AV:	☐	☐	☐	☐	☐	☐	☐	☐	☐
CAV	☐	☐	☐	☐	☐	☐	☐	☐	☐

(2) Fuel saving:

	-30%	-20%	-10%	0	10%	20%	30%	40%	50%
AV:	☐	☐	☐	☐	☐	☐	☐	☐	☐
CAV	☐	☐	☐	☐	☐	☐	☐	☐	☐

(3) Safety improvements:

	-30%	-20%	-10%	0	10%	20%	30%	40%	50%
AV:	☐	☐	☐	☐	☐	☐	☐	☐	☐
CAV	☐	☐	☐	☐	☐	☐	☐	☐	☐

14. If you purchase a new vehicle, how much extra money you are willing to pay at maximum for the AV/CAV tech pack?

	0	$500	$1000	$1500	$2000	$2500	$3000	$3500	$4000	$4500
AV:	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
CAV:	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

15. Any other suggestions:

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