

## Effect of riding experience on changing opinions toward connected and autonomous vehicle safety – Evidence from field experiments

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### ABSTRACT

Connected and autonomous vehicles (CAVs) are considered one of the most promising mobility technologies to be implemented in the near future. A recent study (Shi et al. 2021) investigated how riding experience influences perceptions of autonomous vehicle safety through field experiments. This study used the same dataset as Shi et al. (2021) but focused on investigating the factors influencing people's initial opinions toward CAV safety and how these opinions will change following a successful CAV ride. A random parameter ordered probit model was adopted to analyze people's initial opinions before the CAV ride, which resolves the fixed parameter estimations limitation of the traditional ordered probit model. Furthermore, a hierarchical ordered probit model was used to study people's opinion changes after experiencing the CAV ride, overcoming the fixed thresholds limitation of the traditional ordered probit model. Based on the estimation results, we identified the characteristics of prospective CAV users, such as individuals who drive alone, have Auto Pilot ride experience, have high income, have a long commute time, and have high education levels. Therefore, the needs of these demographics should be well considered in future CAV technology development. We also found that high-education individuals tend to have more negative initial opinions regarding CAV safety compared with others. However, their opinions are more likely to shift toward the positive side after experiencing a successful test ride. In addition, we found that although CAV technologies can enhance traffic efficiency through communication with traffic signals, this improvement may raise people's concerns about the safety of CAVs. The results obtained from this research provide valuable managerial and regulatory insights for the future development and popularization of CAV technologies.

### 1. Introduction

Connected and autonomous vehicle (CAV) technologies have seen rapid development in recent years (Elliott, Keen, & Miao, 2018; Ye & Yamamoto, 2018). Numerous studies have highlighted the merits of CAVs in optimizing road capacity (Guerrieri, 2021; Shi & Li, 2021), alleviating traffic congestion (Ramezani & Ye, 2019), enhancing vehicle safety (Elliott et al., 2018), and reducing environmental pollution (Do, Rouhani, & Miranda-Moreno, 2019; Seuwou, Banissi, & Ubakanma, 2020; Ghiasi, Li, & Ma, 2019). Thus, CAVs have the potential to fundamentally change the existing transportation system (Nikitas, Njoya, & Dani, 2019) as well as people's daily

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lives.

Among these merits, safety enhancement is considered the most critical benefit of CAVs. Because CAVs are controlled by precise and fast-responding sensors, human drivers typically exhibit uncertain and slow-responding behaviors. Thus, it is widely believed that CAVs can significantly reduce accidents caused by human errors (Papadoulis, Quddus, & Imprailou, 2019). Supported by the survey conducted by Schoettle and Sivak (2014), 70 % of 1533 participants believe that crash reduction is the most important benefit of this new technology.

Thus, understanding current opinions about CAVs, particularly regarding safety, is essential to ensure the developed CAVs truly meet people's expectations. Thanks to the rapid development of CAV technologies, a few CAV pilots have been deployed in the real world for testing and demonstration, e.g., U.S. CAV Pilots (USDOT, 2024), which play an important role in the development as well as deployment of the technologies. Although these CAV pilots have been operated for several years and many participants have experienced CAV rides, to the best of the authors' knowledge, few pilots have reported participants' safety perceptions about the demonstrated CAV technologies. In addition to these CAV pilots, some industrial companies and research institutions have also provided CAV demonstrations to the public (Waymo, 2024; Wireless, 2024; Cruise, 2024, etc.). Although participants' opinions may be collected during the demonstrations, no reports or articles that detail the factors influencing public perception of safety are available online.

Thus, to fill this gap, our lab conducted a real-world CAV demonstration at the 2019 Florida Automated Vehicles (FAV) Summit. Participants' opinions toward CAV safety were collected before and after providing a CAV ride. Then, a few discrete statistical models were adopted to study the factors influencing people's initial opinions toward CAV safety and how these opinions will change following a successful CAV ride. The results obtained from this study can provide valuable managerial and regulatory insights for the future implementation and popularization of CAV technologies.

Overall, the main contributions of this research are as follows:

1. To the best of the authors' knowledge, this work for the first time investigated participants' opinions toward CAV safety by providing field CAV rides in the literature. Contradicted findings were noticed by comparing our findings with those from studies without field experiments, which consolidates the contribution of our paper and emphasizes the importance of field experiments when studying participants' opinions toward emerging mobility technologies
2. We found that a successful CAV ride experience will influence participants' opinions toward the technologies. Thus, this research explicitly studied the factors influencing people's initial opinions and opinion changes toward CAV safety after providing a successful CAV ride
3. According to the model estimation results, this paper identified the characteristics of potential CAV user groups and provided valuable guidance for selecting demonstration sites to accelerate technology adoption. Additionally, this paper highlights participants' concerns regarding specific CAV features, underscoring the need to design and develop safety-related features carefully

The remaining parts of this paper are organized as follows: Section 2 reviews the relevant studies in the literature. Section 3 presents the experimental procedures, data and statistical models adopted in this paper. Section 4 shows the estimation results of participants' initial opinions and opinion changes on CAV safety. Section 5 summarizes the conclusion and provides future directions.

**Table 1**  
Relevant CAV studies in the literature.

Reference	Number of participants	Survey type	Model	Location	Main findings
Lee and Hess (2022)	914	Online survey	Ordered logistic regression model	US	<ul style="list-style-type: none"> <li>• Women are more concerned about safety</li> <li>• People older than 60 are more concerned about safety</li> <li>• Non-Whites are more concerned about safety</li> </ul>
Kim, Park, Oh, Lee, and Chung (2019)	Consumers: 98 Experts: 46	Online survey	Analytic hierarchy process	Korea	<ul style="list-style-type: none"> <li>• Safety attributes as the most important benefit and concern in common</li> <li>• Consumers prioritize convenience and costs</li> <li>• Experts focus on social impacts</li> </ul>
Ahmed, Iqbal, Karyotis, Palade, and Amin (2022)	235	Online survey	Machine Learning Prediction Models	UK	<ul style="list-style-type: none"> <li>• Users' concerns about CAV focus on safety, trust, privacy, accessibility, ethics</li> </ul>
Havlíčková, Gabrel, Adamovská, and Zámečník (2019)	1, 116	Online survey	Distribution analysis	Czech	<ul style="list-style-type: none"> <li>• Women are more neutral or negative toward CAVs</li> <li>• Older people are less willing to adopt CAV</li> </ul>
Sharma and Mishra (2020)	327	Online survey	Integrated choice and latent variable model	US	<ul style="list-style-type: none"> <li>• High-income, frequent car buyers likely to adopt CAV</li> <li>• CAV adoption boosts social values among peers</li> </ul>
Vít, Stanislav, and Darina (2019)	1, 065	Online survey	Descriptive statistics and bivariate analyses	Czech	<ul style="list-style-type: none"> <li>• The majority links CAVs to safer traffic</li> <li>• Skepticism from older, less-educated, lower-income groups</li> </ul>
Kong et al. (2024)	339	Online survey	Latent profile analysis and multinomial logit model	China	<ul style="list-style-type: none"> <li>• Lower-income, experienced drivers are often skeptical</li> </ul>

## 2. Literature review

Most researchers studied people's opinions toward CAVs through pure surveys (e.g., road surveys, online surveys, etc.) rather than collecting survey data after conducting field experiments. Pure-survey-based studies typically have more observations than field-experiment-based studies, as the data collection process is more efficient. With the rich number of observations, the results of pure-survey-based studies are usually more general and comprehensive. For example, [Kacperski, Kutzner, and Vogel \(2021\)](#) surveyed 529 participants from France, Germany, Italy, and the United Kingdom on roads to study people's opinions toward CAV safety. Most participants believed that CAV would positively impact safety, with participants from Italy expecting a higher level of safety than those from Germany, France and the United Kingdom. [Bansal and Kockelman \(2018\)](#) conducted an online survey encompassing 1,088 respondents in Texas. It was observed that seasoned drivers and older individuals exhibited a lower propensity to invest in new vehicular technologies. Conversely, individuals with higher income levels and a more safety-conscious approach demonstrated greater support for emerging vehicular technologies. Moreover, [Bansal, Kockelman, and Singh \(2016\)](#) conducted another online survey on 347 Austinites, revealing that urban-dwelling, high income, tech-savvy males, particularly those who have encountered more frequent collisions, exhibit a heightened interest in novel vehicle technologies, but older individuals appear less enthusiastic about those technologies. [Table 1](#) summarizes the existing literature on participants' opinions toward CAVs, highlighting that most studies primarily use survey-based methods. Despite the success of these studies, it is important to note that the majority of participants have never experienced a real CAV ride. Given that these studies often provide only basic information about CAV technologies, e.g., introductory images and texts, questions remain about the accuracy of these findings in reflecting real participants' opinions.

To address the limitations inherent in purely survey-based approaches, limited studies in the literature explored people's opinions toward CAVs by collecting survey data after conducting field experiments. The most relevant study for our research is [Dennis, Paz, and Yigitcanlar \(2021\)](#), which interviewed 153 participants who had ridden a CAV in Las Vegas and 236 participants who had not. They aimed to study whether a past CAV riding experience can benefit people's opinions toward CAV technologies. It was found that people who had been exposed to CAVs felt more positive than those who had not. This result again suggests that riding experience can lead to participants' opinion shift and deserves further investigation. As they could not capture participants' opinions before the CAV ride, this study, despite being a leading effort in the field, did not explicitly analyze how the riding experience influences changes in opinion or identify the factors that govern these opinion changes.

While studies exploring people's opinions toward CAV safety both before and after experiencing a CAV ride are limited, the field of Autonomous Vehicles (AVs) offers a wealth of research ([Cunningham, Regan, Horberry, Weeratunga, & Dixit, 2019](#); [Eden, Nanchen, Ramseyer, & Evéquoz, 2017](#); [Mahmoodi Nesheli, Li, Palm, & Shalaby, 2021](#); [Morra, Lamberti, Gabriele Pratico, Rosa, & Montuschi, 2019](#); [Salonen, 2018](#)). The key distinction between AVs and CAVs can be found in the footnote.<sup>1</sup> This body of work can provide valuable insights for our study. For example, [Shi, Wang, Li, and Pei \(2021\)](#) studied 166 participants' initial opinions toward AV safety, finding changed opinions after providing a successful AV ride. Factors such as people's age, personal income, monthly fuel cost, daily commute time, etc., may dominate people's opinion change after a successful AV ride. Similarly, 300 students were invited to experience an AV by [Xu et al. \(2018\)](#) and [Liu and Xu \(2020\)](#). After providing AV rides to the participants, it was found that a successful AV experience can significantly increase participants' trust in AV. This common finding further illustrates the importance of studying people's perceptions of CAV technologies with real-world experiments and examining the opinion changes after providing a successful ride.

In summary, there is a lack of studies investigating people's opinions and opinion changes, particularly toward CAVs, using survey data collected from real-world demonstrations. To fill this gap, this work adopted the ordered probit model and a few of its variants to study the factors determining the likelihood of participants' initial opinions and opinion changes regarding CAV safety. The results of this study will provide valuable insights into policymakers' and mobility managers' management and supervision of emerging mobility technologies.

## 3. Method

### 3.1. Experimental procedures

To study participants' opinions before and after having a successful CAV ride, this research used data from a field survey conducted at the 2019 FAV Summit during an AV/CAV demonstration. The vehicle used in this demonstration was developed by the Connected and Autonomous Transportation System (CATS) lab at the University of Wisconsin-Madison. This vehicle is modified from a Lincoln MKZ 2016 Hybrid and equipped with various sensors (e.g., LiDAR, radar, cameras, etc.) to perceive its surrounding environment. This vehicle is designed to function as both an AV and a CAV by enabling or disabling its communication functions (an onboard unit that

<sup>1</sup> The key distinction between AVs and CAVs lies in their communication capabilities with surrounding vehicles and infrastructure. Like human drivers, AVs can only plan their trajectories (i.e., motion behaviors) based on information perceived by their onboard sensors (i.e., vision ranges of human drivers). With the communication capability, CAVs can receive extensive information (e.g., traffic signal timing plan, other vehicles' motion information) beyond their own perception ranges from other entities within the environment. This additional information can be incorporated into CAVs' trajectory planning modules, enabling CAVs to achieve superior performance (e.g., safety, energy efficiency, driving comfort) compared to AVs, e.g., by incorporating real-time traffic signal timing data, CAVs can optimize their speed to pass through multiple intersections without stopping, thereby reducing energy consumption and improving passenger comfort.

facilitates communication with the roadside unit mounted on the portable traffic signal, enabling its CAV capabilities). The test vehicle and portable traffic signal with the roadside unit are shown in [Fig. 1](#).

[Fig. 2](#) shows the schematic diagram of the demonstration. The vehicle will follow a predefined path starting from location A and heading to location D. Along the path, there is a portable traffic signal located at location B, and the vehicle will make a U-turn at location C. The overall path length is about 200 m. Each demonstration can accommodate 1 to 4 participants, including two rounds, an AV round and a CAV round. In the AV round, the vehicle will operate following the traffic signal at location B. In other words, when the onboard sensors detect a red traffic signal, the vehicle will stop before the stop line. Once the traffic signal turns green, the vehicle will proceed through it. In the CAV round, the vehicle can communicate with the traffic signal through a Dedicated Short-Range Communication (DSRC) unit. Thus, when approaching the traffic signal, a signal request will be sent to the signal and thus force the traffic signal to change to green. In this way, the vehicle can always pass through the traffic signal without stopping. It is clear that the CAV round will provide participants with a better travel experience than the AV round, given the smoother speed profile of the CAV round. During the demonstration, a human driver was always seated in the driver's seat for real-time monitoring of the CAV/AV. If anything unexpected happens in the CAV/AV ride, the human driver will promptly take control of the vehicle to ensure safe driving.

Before participating in the demonstration ride, recorders will explain the guidelines and precautions for completing the survey questionnaire to the participants, and participants will be asked to complete questionnaires regarding their demographics and initial opinions toward AV/CAV safety. After taking the ride, participants will be asked to record their opinions again and return the questionnaires to the recorders.

### 3.2. Data

Data from 166 participants were collected, out of which 159 were considered valid (without missing fields) and will be used for further analysis. It is worth noting that the participants in this experiment exhibited a higher age, level of CAV technologies knowledge and individual annual income than the US population. The median age of the US resident population in 2019 was 38.1 ([Demographics, 2019](#)), but the average and median age in this study is 43 higher than the US median. This bias is due to the majority of participants being conference attendees, who may be experts in the transportation area, tend to be better educated, more exposed to transportation-related topics, and have higher age than the population. Despite this bias, the participants were randomly distributed across the population and are likely to be among the first individuals to embrace CAV technologies. Therefore, studying their views on the safety of CAV technologies is valuable for further research in this area.

The survey data comprises three types of information. The first part includes participants' basic information, such as demographic details, daily commuting habits, prior experience with emerging automotive technologies, and more. The second part captures participants' opinions about the safety of AV/CAV technologies before they experience the ride. The final part records participants' opinions on the safety of AV/CAV after the ride. Descriptive statistics for those variables that were found to be statistically significant determinants of people's opinions toward CAV safety can be found in [Table 2](#).

Participants were asked to state their views on a five-point scale of "strongly disagree," "disagree," "neutral," "agree" and "strongly agree." The questionnaire used in this experiment is shown in Appendix A. Upon analyzing the collected data, it was observed that participants did not provide any "strongly disagree" opinions regarding CAV technologies, both before and after taking CAV rides. The frequencies of opinions before and after the CAV rides are presented in [Table 3](#). Therefore, only four opinion categories of CAV technology safety are studied in the following models.

Initial opinions are likely to be critical determinants of final opinions and serve as a guide to any change in these opinions, also known as the anchoring effects ([Kahneman & Tversky, 1974](#); [Sheela & Mannering, 2019](#)). Thus, in the after-ride model, attention was given to studying opinion changes condition on their initial opinions. Specifically, for those individuals who initially indicated "disagree," "neutral," "agree," and "strongly agree" that CAV is safe, we will study how their opinion changes after having a successful CAV ride. To achieve this, participants' after-ride opinions are categorized into three groups based on their initial opinions: "negatively changed," "unchanged," and "positively changed." Here is an illustrative example to clarify this process: Suppose a respondent's initial opinion was "agree." after the CAV ride, if their opinion changes to "disagree" or "neutral", it will be classified as a "negatively changed" case. If their opinion changes to "strongly agree", it will be considered a "positively changed" case. If their opinion remains the same (e.g., still "agree"), it will be treated as an "unchanged" case. The results of the frequency of opinion changes can be found in



**Fig. 1.** Test CAV developed by the CATS lab and portable traffic signal with the roadside unit.

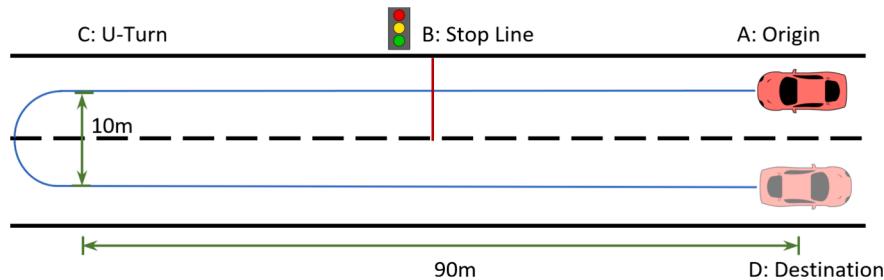


Fig. 2. Test path schematic diagram of the CAV ride.

Table 2

Descriptive statistics of key variables.

Variable description	Mean	Std. Dev.	Min	Max
Participant's age	43.04	12.90	21.00	71.00
High education indicator (1 if participant holds a master's degree or above, 0 otherwise)	0.52	0.50	0.00	1.00
High income indicator (1 if participant's annual personal income is greater than \$140,000, 0 otherwise)	0.26	0.44	0.00	1.00
Long commute time indicator (1 if participant's commute time is greater than 19 min, 0 otherwise)	0.74	0.44	0.00	1.00
Drive alone indicator (1 if participant drives alone to commute, 0 otherwise)	0.87	0.34	0.00	1.00
Participant's monthly fuel cost (unit: USD)	123.43	85.83	0.00	300.00
Auto Pilot (Adaptive cruise control) ride experience indicator (1 if participant ever had Auto Pilot ride experience, 0 otherwise)	0.40	0.49	0.00	1.00
High extra money willing to pay for CAV tech pack indicator (1 if participant wants to pay for CAV tech pack more than \$3500, 0 otherwise)	0.36	0.48	0.00	1.00

Table 3

Initial opinion and opinion change frequency.

After	Before					Total
	Disagree	Neutral	Agree	Strongly agree		
Disagree	2×	4 ↓	2 ↓	0 ↓		8
Neutral	4↑	16×	8 ↓	4 ↓		32
Agree	4↑	15↑	35×	10↓		64
Strongly Agree	0↑	12↑	16↑	27×		55
Total	10	47	61	41		159

Note: ↑ represents positively changed; × represents unchanged; ↓ represents negatively changed.

Table 3. According to the results, after having a successful CAV ride, 51 out of 159 participants' opinions shifted to the positive side, while 28 out of 159 shifted to the negative side, and 80 participants' opinions remained the same.

### 3.3. Methodological approaches

With these results, we model the factors determining the likelihood of participants' initial opinions and opinions shifting from their initial opinions about CAVs' safety. Due to the ordinal nature of people's opinions toward safety, the ordered probit model with a few of its variants is adopted to study the collected data (Washington et al., 2011). The traditional ordered probability model was specified by defining an unobservable variable  $z$  as a linear function for each respondent  $i$ ,

$$z_i = \beta X_i + \varepsilon_i,$$

where  $X_i$  is the vector of explanatory variable that determines the discrete answer of participant  $i$ ,  $\beta$  is the vector of estimable parameters, and  $\varepsilon_i$  is a random error term that is assumed to be normally distributed with a mean equal to zero and variance equal to one. The observed ordinal data  $y$ , i.e., people's opinion toward safety before and after the test ride, can be determined as below (Washington et al., 2011):

$$y_i = j, \text{ if } \mu_{j-1} < y_i < \mu_j, j = 1, 2, \dots, J,$$

where  $\mu$  are threshold parameters;  $y$  and  $j$  denote the ordered ranking of people's opinion toward safety such as "disagree," "neutral," "agree," and "strongly agree" in the before-ride model, and "negatively changed," "unchanged," and "positively changed" in the after-ride model.

In the traditional ordered probit model, the estimated thresholds (i.e.,  $\mu_j$ ) and parameters (i.e.,  $\beta$ ) are assumed to be fixed across the observations. Due to possible unobserved heterogeneities (unobserved factors that may vary across observations), this fixed estimation result assumption may not always hold. Failing to capture the threshold heterogeneity and unobserved heterogeneity may easily cause model misspecification and thus lead to incorrect results. To overcome the potential issues, the hierarchical ordered probit (HOPIT) model, random parameters ordered probit model, and random parameters hierarchical ordered probit are also studied.

The HOPIT model allows thresholds to be varied as a function of a few explanatory parameters, which can be expressed as follows (Greene & Hensher, 2010):

$$\mu_{ij} = \mu_{ij-1} + \exp(t_j + d_j S_i),$$

where  $t$  is the intercept for each threshold,  $S$  are vectors of variables affecting the thresholds, and  $d$  are vectors of estimable parameters for  $S$ .

The random parameter methods (Washington et al., 2020) allow the estimated parameters to vary among different observations. Estimable parameters can be written as values,

$$\beta_n = \beta + w_n,$$

where  $\beta_n$  is a vector of estimable parameters that may vary between different observations  $n$ ,  $\beta$  is a vector of average parameter estimates for all observations, and  $w_n$  is a vector of random distribution terms (e.g., normal distribution terms with mean 0 and variance  $\sigma^2$ ).

The random parameters HOPIT model combines the advantages of the HOPIT model and random parameter methods by allowing both thresholds and parameters to vary simultaneously, providing more flexibility to the model.

In this context, the ordered probit model of each different opinion level  $j$  for each observation can be calculated as:

$$P(y = j) = \Phi(\mu_j - \beta_i X_i) - \Phi(\mu_{j+1} - \beta_i X_i)$$

where  $P(y = j)$  is the probability of the opinion level  $j$ ,  $\Phi(\cdot)$  is the cumulative normal distribution. Note that for the first opinion outcome ( $j = 1$ ), the corresponding threshold ( $\mu_0$ ) is specified as zero without loss of generality. This indicates that only  $J-2$  thresholds will be estimated (e.g., two thresholds for the before-ride model and one threshold for the after-ride model).

To assess the effect that a unit change in the explanatory variables on people's opinion toward CAV safety, this paper computes the marginal effects according to the following equations,

$$\frac{P(y = j)}{\partial X} = [\Phi(\mu_{j-1} - \beta X) - \Phi(\mu_j - \beta X)] \beta$$

In addition, the ordered probit of random parameters is estimated by the simulated maximum likelihood method. Compared with pure random draws, Halton draws produce a more efficient simulated draw distribution (Bhat, 2003). One thousand Halton draws have been shown to provide accurate parameter estimates when simulating likelihood functions (Halton, 1960). As a result, this number is used for model estimates in this paper.

### 3.4. Parameters transferability test

To establish that participants' opinions were not stable between their initial assessment of CAV safety and their final assessment (after having a successful CAV ride), estimation results from three ordered probit models were used: a before-ride model (opinions before the CAV ride estimated), an after-ride model (opinions after having the CAV ride), and an overall model that includes opinions both before and after the CAV ride. With these model estimates, a likelihood ratio test was conducted as  $\chi^2 = -2[LL(\beta)_{\text{combined}} - LL(\beta)_{\text{before}} - LL(\beta)_{\text{after}}]$ , where  $LL(\beta)_{\text{combined}}$  is the log-likelihood at the convergence of a model using the data from both before and after providing the CAV ride,  $LL(\beta)_{\text{before}}$  is the log-likelihood at the convergence of a model estimated before providing the CAV ride, and  $LL(\beta)_{\text{after}}$  is the log-likelihood at the convergence of a model after providing the CAV ride. The resulting  $\chi^2$  statistic was found to be 25.806, and 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 12. This  $\chi^2$  value suggests that there is more than 98.86% confidence that the before and after parameter values were not the same, suggesting that the CAV ride experience was significantly affecting individual opinions on CAVs' safety, which is consistent with our expectations.

## 4. Estimation results

### 4.1. Initial opinion (before-ride) model

The fixed parameters ordered probit model (Log-Likelihood: -185.163), HOPIT model (Log-Likelihood: -184.868), random parameters ordered probit model (Log-Likelihood: -183.965), and random parameters HOPIT model (Log-Likelihood: -184.085) were used to study participants' initial opinions. The estimation results show that the random parameters ordered probit model possesses the largest Log-Likelihood value. Thus, it is identified as the best model in terms of model fitness. Table 4 shows the result of the

random parameters ordered probit model for the initial opinions toward CAV safety, and the average marginal effects for this model are shown in Table 5. It can be found that a total of seven variables in Tables 4 and 5 significantly affect the initial opinion of participants.

The *long commute indicator* variable and the *high education indicator* variable provide normally distributed random parameters with statistically significant standard deviations, indicating significant unobserved heterogeneity between participants. The mean and standard deviation for random parameters determine the distribution of the random parameter values (above and below 0, respectively). The *long commute indicator* variable identifies participants whose commute time is greater than 19 min. The random parameters mean and standard deviation of the long commute indicator are 0.526 and 1.131, respectively. Since the random parameter is normally distributed, it can be calculated that the result above 0 is 67.91 % and below 0 is 32.09 %, which indicates that the effect of this variable increased the likelihood of strongly agreeing to the safety of the CAVs by 67.91 % of participants and decreased it by 32.09 %. For several reasons, participants with long daily commute times might strongly believe in CAVs' safety. First, they often face fatigue from long driving times on the road, making the consistent vigilance of CAVs highly attractive. Second, the reduction of stress and the opportunity to use travel time more productively without the need to concentrate on driving are also significant advantages. Third, the economic benefits, including cost savings and less physical strain, alongside the environmental benefits of optimized driving patterns, contribute to their positive perception of CAV safety. They may be the potential users of CAV technology.

The *high education indicator* describes the participant who holds a master's degree or above. The random parameters mean and standard deviation of this variable are -0.415 and 0.549 (above 0 is 22.48 % and below 0 is 77.52 %), indicating that the effect of this variable increased 22.48 % of highly educated participants the likelihood of strongly agreeing to the safety of the CAVs. The other 77.52 % of highly educated participants were less likely to strongly agree that CAVs were safe. This may be because participants with higher education levels may exhibit more skepticism toward the safety of CAVs due to their tendency for critical analysis and heightened awareness of the technologies. Their education may lead them to be more cautious and less trusting of the safety claims of CAVs until there is significant evidence to support those claims.

Tables 4 and 5 show that the participant whose annual personal income is greater than \$140,000 has a lower probability of agreeing or strongly agreeing with CAV safety. This may be because people with higher incomes are more critical of the safety of CAV technologies and have reservations about them until there is strong evidence that they are safe. The increase in participants' monthly fuel cost will decrease the initial opinions toward CAVs' safety. This may be because people with higher monthly fuel costs experience more complex road conditions and are less confident that CAVs can handle the complex traffic conditions on the road.

The participants who had Auto Pilot ride experience and drove alone when commuting had higher probabilities of "agree" or "strongly agree" to the safety of the CAV technologies. These people will probably be the first consumers of CAV technologies. The older a participant is, the more likely they are to hold an initial "agree" or "strongly agree" opinion about the safety of the CAVs. This may be because most of the participants were conference attendees who were significantly more educated and exposed to CAV technologies, so they were more convinced of the security enhancements that CAV technologies bring.

#### 4.2. Opinion changes (after-ride) model

The same with the initial opinions, due to the ordinal nature of the opinion change results (i.e., "negatively changed," "unchanged," and "positively changed"), the ordered probit model is again used to estimate participants' opinion changes after being provided a successful CAV ride.

We fitted the collected data to different types of ordered probit models, including the fixed parameters ordered probit model (Log-

**Table 4**

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

Variable description	Estimated parameter	t statistic
Constant	0.130	0.30
Long commute time indicator (1 if participant's commute time is greater than 19 min, 0 otherwise)(standard deviation of parameter distribution)	0.526** (1.131***)	2.34 (7.97)
High education indicator (1 if participant holds a master's degree or above, 0 otherwise)(standard deviation of parameter distribution)	-0.415** (0.549***)	-2.22 (4.03)
Participant's age	0.029***	3.44
High income indicator (1 if participant's annual personal income is greater than \$140,000, 0 otherwise)	-0.444*	-1.75
Drive alone indicator (1 if participant drives alone to commute, 0 otherwise)	1.317***	4.51
Auto Pilot (Adaptive cruise control) ride experience indicator (1 if participant ever had Auto Pilot ride experience, 0 otherwise)	0.711***	3.46
Participant's monthly fuel cost (unit: USD)	-0.390***	-3.07
Threshold 1	1.795***	7.31
Threshold 2	3.412***	11.31
Number of observations	159	
Log-likelihood at zero [LL(0)]	-274.745	
Log-likelihood at convergence [LL(β)]	-183.965	
$\rho^2 [1 - LL(\beta) / LL(0)]$	0.330	

Note: \*\*\*, \*\*, \* means significance at 1%, 5%, 10% level.

**Table 5**

Average marginal effects for the initial opinions toward CAV safety model.

Variable description	Marginal effects			
	Disagree	Neutral	Agree	Strongly agree
Participant's age	-0.0007	-0.0091	0.0028	0.0070
High income indicator (1 if participant's annual personal income is greater than \$140,000, 0 otherwise)	0.0133	0.1425	-0.0612	-0.0946
Drive alone indicator (1 if participant drives alone to commute, 0 otherwise)	-0.0997	-0.3870	0.3020	0.1847
Participant's monthly fuel cost (unit: USD)	0.0088	0.1210	-0.0370	-0.0930
Auto Pilot (Adaptive cruise control) ride experience indicator (1 if participant ever had Auto Pilot ride experience, 0 otherwise)	-0.0150	-0.2088	0.0428	0.1810
Long commute time indicator (1 if participant's commute time is greater than 19 min, 0 otherwise)	-0.0166	-0.1689	0.0755	0.1101
High education indicator (1 if participant holds a master's degree or above, 0 otherwise)	0.0095	0.1272	-0.0369	-0.0998

Likelihood: -151.837), the HOPIT model (Log-Likelihood: -144.144), the random parameters ordered probit model (Log-Likelihood: -151.827), and the random parameters HOPIT model (Log-Likelihood: -151.828). We found that the HOPIT model performed best across all the alternative models (i.e., the HOPIT model exhibits the highest Log-Likelihood value) and thus selected it the final model to study participants' opinion changes toward CAVs' safety after taking a successful CAV ride. The estimation results of the HOPIT model are shown in Table 6. The average marginal effects for this model are shown in Table 7. It can be observed that a total of 5 variables are found to significantly affect the people's opinion changes after taking the test ride. The variable, *participant's monthly fuel cost*, is found to influence the threshold parameter across the observations negatively and thus will increase the likelihood for positive opinion changes, which captures threshold-specific unobserved heterogeneity.

Among the four variables resulting in statistically significant fixed parameters (i.e., their effect remains constant across the observations), three variables are also found statistically significant in the before-ride model: *high education indicator*, *Auto Pilot ride experience indicator*, and *drive alone indicator*. Interestingly, the influences of all these three variables on the initial opinion and opinion changes are contradicted by each other. In the before-ride model, it is found that high-education respondents tend to provide a more negative initial opinion than those with a bachelor's or lower education level. However, based on the result shown in Table 6, after a successful CAV test ride, this group of people tends to positively change their opinion toward CAV safety. One possible reason is that the high-education group relatively easily accepts new concepts and carefully scrutinizes their practical applications and implications. This understanding of their behavior may help vehicle vendors select the most suitable sites for showcasing CAVs. By targeting areas with a higher density of educated individuals, vendors might find an audience that is receptive yet critical, providing valuable feedback that can help refine the technology and build trust in its safety, thus aiding in the effort to popularize these advanced vehicles.

On the contrary, the *Auto Pilot ride experience indicator* has totally different results compared with the *high-education indicator*. In the before-ride model, it was found that the respondents who had Auto Pilot ride experience before tended to provide a more positive initial opinion than those who did not have the experience. However, in the after-ride model, this group tends to change their opinion toward CAV safety negatively. The technological difference between AVs and CAVs may explain this. In AV technologies, the vehicle reacts to the traffic signal through the perception system (e.g., camera). The vehicle will plan its behavior once the traffic signal is detected. Thus, there is a delay between when the traffic signal is detected and when the vehicle executes the behavior. However, for CAV technologies, the vehicle will know the traffic signal timing beforehand through vehicle-to-infrastructure communication technologies. Thus, the future behavior of the vehicle will be planned before the vehicle arrives at the traffic signal. The vehicle and the traffic signal will cooperatively operate and thus the delay will be minimized. This will lead to the CAV not decelerating while

**Table 6**

Hierarchical ordered probit model of CAV safety opinion changes after taking the demonstration ride [dependent variable responses are integers between 1 (negatively changed) to 3 (positively changed)].

Variable description	Estimated parameter	t statistic
Constant	1.465***	3.63
High education indicator (1 if participant holds a master's degree or above, 0 otherwise)	0.745***	3.95
Auto Pilot (Adaptive cruise control) ride experience indicator (1 if participant ever had Auto Pilot ride experience, 0 otherwise)	-0.318*	-1.69
Drive alone indicator (1 if participant drives alone to commute, 0 otherwise)	-0.635*	-1.71
High extra money willing to pay for CAV tech pack indicator (1 if participant wants to pay for CDA tech pack more than \$3500, 0 otherwise)	-0.335*	-1.67
<i>Threshold Parameters</i>		
$\mu$	0.892***	6.47
<i>Threshold Parameters Decomposition</i>		
Participant's monthly fuel cost (unit: USD)	-0.004***	-3.66
Number of observations	159	
Log-likelihood at zero [LL(0)]	-301.912	
Log-likelihood at convergence [LL( $\beta$ )]	-144.144	
$\rho^2$ [1 - LL( $\beta$ ) / LL(0)]	0.523	

Note: \*\*\*, \*\*, \* means significance at 1%, 5%, 10% level.

**Table 7**

Average marginal effects for the CAV safety opinion changes after taking the demonstration ride.

Variable description	Marginal effects		
	Negatively changed	Unchanged	Positively changed
High education indicator (1 if participant holds a master's degree or above, 0 otherwise)	−0.1735	−0.0827	0.2562
Auto Pilot (Adaptive cruise control) ride experience indicator (1 if participant ever had Auto Pilot ride experience, 0 otherwise)	0.0750	0.0349	−0.1099
Drive alone indicator (1 if participant drives alone to commute, 0 otherwise)	0.1115	0.1293	−0.2408
High extra money willing to pay for CAV tech pack indicator (1 if participant wants to pay for CDA tech pack more than \$3500, 0 otherwise)	0.0804	0.0344	−0.1148

approaching the traffic signal when it is in red since the vehicle knows that the traffic signal will turn green when it arrives. Thus, this may cause people to feel that driving is “dangerous” and they will change their opinion negatively.

The influence of the *driving alone indicator* is similar to the *Auto Pilot ride experience indicator*. In the before-ride model, the respondents who drive alone to commute will have a more positive initial opinion than others. However, in the after-ride model, this group tends to change their opinion toward CAV safety negatively. The respondents who drive alone may have more concerns about driving safety since no one is with them to help monitor road conditions. Thus, it is reasonable that they are concerned about the CAV technologies toward safety because the CAV ride provided to them is still immature. This finding may reveal one potential target customer group for emerging mobility technologies (e.g., CAVs): those who drive alone. Their expectation about CAVs’ safety should be considered while developing the technologies.

The remaining variable that significantly affects the participants’ opinion changes after taking the test ride is the *high extra money willing to pay for the CAV tech pack indicator* variable. This variable is related to the *high income indicator* variable in the before-ride model. Their influences are the same. In the before-ride model, high income respondents tend to have a worse initial opinion than other respondents. In the after-ride model, as the annual personal income increases, the respondents tend to lower their opinions about CAVs’ safety. This result indicates that people in the high-income group may have a higher expectation of CAVs’ safety than others. After they took the CAV ride, they might find that the performance of the CAV ride cannot satisfy their expectation and thus their opinion changed negatively. Since high income people are considered the first group to adopt CAV technologies, this finding suggests that vehicle vendors should focus more on safety to attract this group of people to purchase their vehicles.

## 5. Conclusions

Safety is always a crucial consideration when adopting new mobility technologies. This study investigated people’s initial opinions and opinion changes regarding the safety of CAVs with survey data collected with real-world CAV demonstrations. The ordered probit model with its variants was employed to study the collected survey data, which yielded intriguing insights into the future popularization and development of CAVs.

In summary, the major findings of this research are as follows:

- People with high incomes are negative in their initial opinion of the safety of CAV technologies. This finding is consistent with the results reported by [Dennis et al. \(2021\)](#). This could be attributed to their higher safety expectations. Since this demographic is still the target group for emerging mobility technologies, it is crucial to design the technologies to meet their safety requirements to deploy the technologies in the market and achieve profitability successfully. Interestingly, this finding contradicted [Kong et al. \(2024\)](#), [Bansal and Kockelman \(2018\)](#) and [Bansal et al. \(2016\)](#), who found that participants with higher income levels exhibit greater support for CAV technology. Since the three mentioned studies were all road-survey-based and did not provide field experiments to participants, this contradiction emphasizes the importance of field experiments when studying participants’ opinions toward emerging mobility technologies. Certainly, it may also be because of the individual differences among the surveyed participants.
- Participants’ ages positively correlate with their initial opinions on CAV safety. This is consistent with the results reported by [Nordhoff et al. \(2018\)](#). However, this finding contrasts with the findings of [Bansal and Kockelman \(2018\)](#) and [Bansal et al. \(2016\)](#). This discrepancy may be because participants in this study, as conference attendees, have higher education levels and greater exposure to CAV technologies, leading them to recognize the safety advantages of CAVs more easily.
- High-education individuals tend to have more negative initial opinions regarding CAV safety compared with others. This aligns with the findings of [Sharma and Mishra \(2022\)](#) about AV. However, their opinions are more likely to shift toward the positive side after experiencing a successful test ride. This insight could assist vehicle vendors in selecting appropriate CAV demonstration sites to promote the technologies effectively.
- People who drive alone or who had an Auto Pilot ride experience with a long commute time are potential users of AV/CAV technologies. [Saeed, Burris, Labi, and Sinha \(2020\)](#) also indicated that individuals with longer commuting times are more inclined to use AVs, likely because those with longer commutes believe they can use the time more efficiently in an AV or CAV by engaging in other activities (working on a laptop, eating, or sleeping). Understanding their expectations and concerns about safety is essential during the development and implementation of these technologies.

- Although CAV technologies can enhance traffic efficiency through communication with traffic signals, this improvement may raise people's concerns about the safety of CAVs. This suggests that technology developers should carefully balance a vehicle's traffic efficiency performance and its safety features to find a "sweet point" that meets user expectations.

Future research can explore several directions to enhance the understanding of people's perceptions toward CAVs and related aspects. First, due to the limited time available for completing the questionnaire (approximately 2–3 min), only a few essential questions were asked during the data collection process, somewhat limiting the depth of analysis. To address this limitation, future studies could conduct the pre-survey part online, enabling the collection of more comprehensive and diverse information. Second, the dataset used in this study captured participants' perceptions regarding both safety and comfort. Notably, preliminary observations suggest a correlation between people's perceptions of safety and comfort. Investigating the relationship between these two factors could provide valuable insights into how they influence each other and impact people's overall acceptance of CAV technologies. Furthermore, expanding the analysis to incorporate different statistical models, such as the multinomial logit model and learning-based models, could offer alternative perspectives and enrich the understanding of the dataset. Last, it must be mentioned that the data used in this research are biased, exhibiting a higher age, level of CAV technologies knowledge, and individual annual income than the US population because most participants were attendees of the 2019 FAV Summit. While participants in this study are likely to be among the first users of CAV technologies, making their perceptions crucial to understand, addressing the challenge of data bias while still gaining meaningful insights into people's perception toward emerging mobility technologies (AV/CAV) presents an interesting research opportunity.

#### CRediT authorship contribution statement

**Yang Li:** Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Xiaowei Shi:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Xiaopeng Li:** Writing – review & editing, Resources, Project administration, Funding acquisition, Data curation.

#### 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.

#### Data availability

Data will be made available on request.

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The review effort and helpful comments from Dr. Fred Mannering at the University of South Florida are acknowledged with great gratitude. This research is sponsored by National Science Foundation Grant # 2313578.

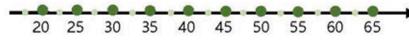
#### Appendix A.: Questionnaire form



Please circle/cross/tick your choice

**Chapter 1: Before your test ride**

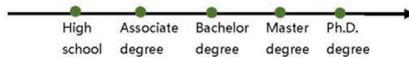
1. Please select your age range:



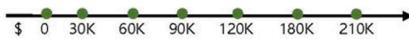
2. Please select your gender:

Female  Male

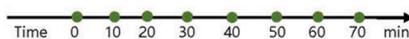
3. Please select your highest education:



4. Please select your annual personal income:



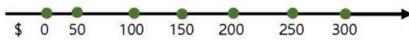
5. Commute time



6. Commute mode

Drive Alone  Share ride  Taxi  
 Public Bus Transit  Rail Transit  
 Walk  Bicycle  Others: \_\_\_\_\_

7. Monthly fuel cost



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

	Yes	No
Adaptive Cruise Control	<input type="checkbox"/>	<input type="checkbox"/>
Automated Lane Keep	<input type="checkbox"/>	<input type="checkbox"/>
Auto Pilot	<input type="checkbox"/>	<input type="checkbox"/>

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

CV: Connected Vehicle

CAV: Connected & Autonomous vehicle



**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%
<input type="checkbox"/>								
AV:	<input type="checkbox"/>							
CAV:	<input type="checkbox"/>							

(2) Fuel saving:

-30%	-20%	-10%	0	10%	20%	30%	40%	50%
<input type="checkbox"/>								
AV:	<input type="checkbox"/>							
CAV:	<input type="checkbox"/>							

(3) Safety improvements:

-30%	-20%	-10%	0	10%	20%	30%	40%	50%
<input type="checkbox"/>								
AV:	<input type="checkbox"/>							
CAV:	<input type="checkbox"/>							

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
<input type="checkbox"/>									
AV:	<input type="checkbox"/>								
CAV:	<input type="checkbox"/>								

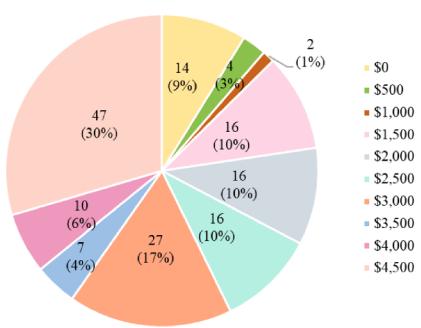
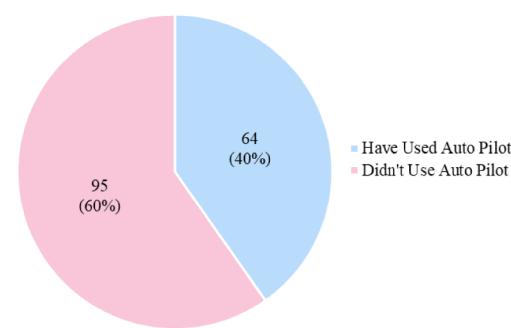
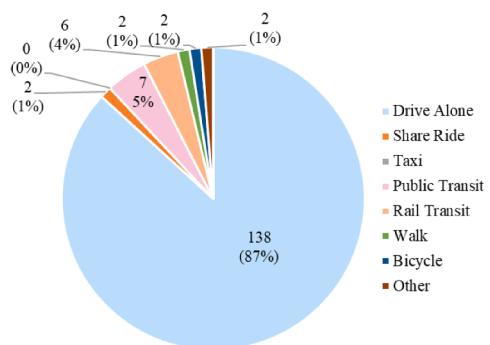
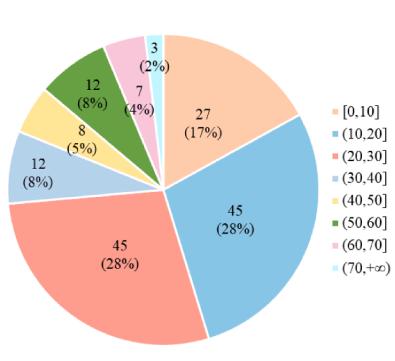
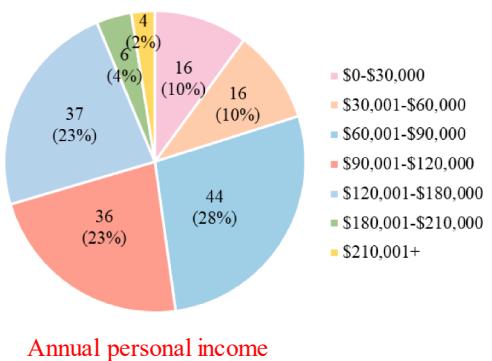
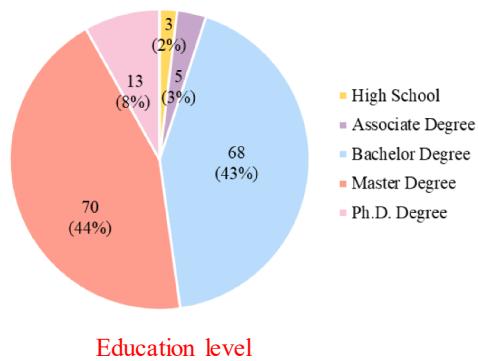
15. Any other suggestions:

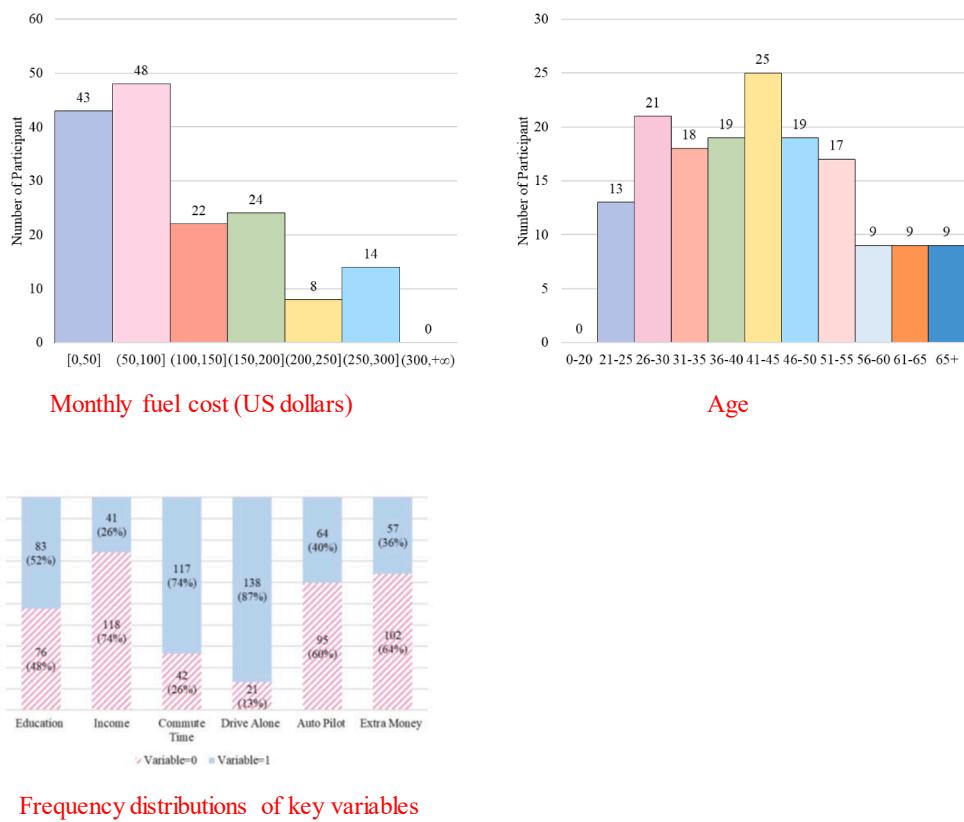
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**Appendix B. Frequency distribution of key answers and variables**





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