Analysis of Safety Benefits and Security Concerns from the Use of Autonomous Vehicles: A Grouped Random Parameters Bivariate Probit Approach with Heterogeneity in Means

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ABSTRACT

This paper investigates public perceptions towards potential safety benefits, and safety- and security-related concerns from the future use of autonomous vehicles by utilizing data collected from an online survey. The survey includes responses from 584 individuals from the United States, who responded to a varying range of questions related to autonomous vehicles and their usage. The subsequent exploratory statistical analysis is conducted by employing a novel method, namely the grouped random parameters bivariate probit model with heterogeneity in means. The proposed method accounts for the challenges stemming from the presence of multiple layers of unobserved heterogeneity in the data, and simultaneously offers more insightful results. From the analysis, several socio-demographic characteristics, and driving attitude related characteristics and opinions were found to affect the perceptions towards the safety and security related aspects of autonomous vehicles. The heterogeneity in means approach revealed distinct individual-specific characteristics that affect the peak of the distribution of the parameter density function of the random parameters, adding further clarity to the understanding of the factors affecting individuals' perceptions towards autonomous vehicles. The findings from this study suggest the ongoing evaluation of public perceptions, and reinforce the requirement of analyzing temporal variations in public perceptions. This can, in turn, aid regulatory and governance entities and autonomous vehicle manufacturers to adapt their strategies and implementation plans accordingly.

Keywords: Autonomous vehicles; Safety; Security; Grouped random parameters; Bivariate probit model; Heterogeneity in means.

1. INTRODUCTION

Technological advancements of the 21st century have enabled the realization of long-awaited autonomous vehicle (AV) technology. To put things into perspective, one of the leading companies in autonomous vehicle technology development, Waymo, has begun providing commercial autonomous vehicle based ridesharing services in Phoenix, AZ, and its surrounding cities since late 2018 (LeBeau, 2018). The electric vehicle manufacturing giant Tesla, Inc., has been offering full self-driving capabilities in all of their production models since 2019, and have demonstrated their autopilot system's capability of providing door-to-door rides (Hawkins, 2019; Baldwin, 2020). The autonomous vehicle revolution is anticipated to improve the overall safety conditions on the roadway, by greatly reducing crashes and consequent fatalities – and in a similar manner reducing injury severity (from severe to minor injuries, to property damage only, to no collision) – the majority of which result from human errors in driving. The reduction and ultimately, elimination of human error from the driving environment, are believed to bring a safer traveling experience for the general population. However, the success of autonomous vehicle technologies in the short and long term ultimately depends on whether the system users are willing to trust and embrace this technology. In addition, the rapid transitional nature of technological advancements, combined with autonomous vehicle related incident information communicated worldwide, appears to lead public perceptions to go through transitional phases: from being skeptical to very enthusiastic, and vice versa. This poses a unique challenge for researchers, regulatory authorities, and manufacturers alike, and mandates continuous assessment of public opinions towards autonomous vehicles.

1.1. Literature Review

Over the last decade, numerous studies have investigated public perceptions and opinions towards autonomous vehicle technologies. The focus of these studies ranges from public willingness to use and pay for autonomous vehicle technologies, to safety and security related benefits/concerns, or to societal and environmental implications. A study by Howard and Dai (2014) based on a survey conducted in Berkeley, CA, revealed that age, gender, and income level affect the individuals' perceptions towards autonomous vehicle technologies. The respondents indicated that the most attractive attribute of autonomous vehicles was the potential safety benefits; whereas, the main concerns involved liabilities and cost aspects of the autonomous vehicle technologies. Individuals from households with annual income less than $50K were found to be most enthusiastic about the safety benefits of autonomous vehicles, as compared to more affluent individuals. Male respondents were also found to be more convinced about the safety benefits of autonomous vehicles, as compared to females.

Schoettle and Sivak (2014) conducted an online survey using respondents from the United States, United Kingdom, and Australia. The analysis revealed that respondents from the United States expressed concerns regarding autonomous vehicle system security, privacy of personal data (location and speed tracking), and autonomous vehicle performance in poor weather conditions. The study also indicated that individuals without a driver's license were less likely to be concerned about the safety aspects of autonomous vehicle technologies. Similarly, Owens et al. (2015) conducted a study with participants from the United States, and focused on evaluating cross-generational (Millennials, Generation X, Baby Boomers and Silent Generation) interests and concerns in advanced vehicle technologies, including autonomous vehicles. The study showed that across all generations, more than 70% of the respondents were concerned not only with the security of autonomous vehicles (e.g., hackers taking over the system and causing traffic jams or crashes), but also with the vulnerability of personal information (hackers stealing personal information). In addition, the percentage of respondents expressing concerns gradually increased from younger generations to older generations. Findings from Kyriakidis et al. (2015) are in agreement with the findings from both Sivak and Schoettle (2015) and Owens et al. (2015).

Bansal et al. (2016) investigated the perceptions of residents from the city of Austin, TX, towards new vehicle technologies including level 4[1] automation of vehicles. The survey results indicated that more than 60% of the respondents were expecting fewer crashes on the roadway with level 4 automation. On the contrary, more than 85% and around 70% of the respondents were slightly to very concerned about equipment or system failure and security issues (hackers taking control of autonomous vehicles, and stealing private information), respectively. In another study that focused on respondents from the state of Texas in the United States (Bansal and Kockelman, 2016), similar patterns of responses were observed. Zmud et al. (2016) conducted a study to evaluate general public's intent to use autonomous vehicles, and identify factors that affect their intent to use, and reasons that discourage them. The results from this study indicated that 24% of the respondents cited safety concern as the reason for not intending to use autonomous vehicles.

[1] The National Highway Traffic Safety Administration (NHTSA) classifies vehicle automation levels as follows (NHTSA, 2017):
Level 1: The driver controls the vehicle, but some driving assist features can help with steering or braking/accelerating (not both at the same time).
Level 2: An advanced driving assist system can control both steering and braking/accelerating, but the driver must pay full attention and perform the remaining driving tasks.
Level 3: An automated driving system (ADS) can perform all driving tasks in some situation. The human driver must be ready to take the control back when required.
Level 4: An automated driving system (ADS) can perform all driving tasks in certain situations without requiring the driver's attention.
Level 5: An automated driving system (ADS) can perform all driving tasks in all situations without requiring human intervention.

Hohenberger et al. (2017) indicated that perceived safety benefits of autonomous vehicles, in terms of reducing traffic crashes and fatalities, have overall positive effect on the willingness to use autonomous vehicles. König and Neumayr (2017) indicated that despite believing in the potential of autonomous vehicles to reduce traffic crashes, individuals held pronounced levels of concern towards attacks from hackers on the autonomous vehicle systems, as well as concerns arising from personal location tracking. Woldeamanuel and Nguyen (2018) focused on evaluating public perceptions towards autonomous vehicles in a Millennials vs. Non-Millennials setting. About 80% of both Millennial and Non-Millennial respondents expected a reduced number of crashes on the roadway with the use of autonomous vehicles. However, perceptions towards concerns arising from the use of autonomous vehicles varied significantly between Millennials and Non-Millennials. Millennials were found to be significantly less concerned about autonomous vehicle system performance in poor weather, equipment or system failure, as well as personal information privacy, as compared to Non-Millennials. Cunningham et al. (2019) surveyed 5,089 respondents from Australia to assess public opinions towards autonomous vehicle technologies. Results from this study showed that females were more concerned about safety issues stemming from autonomous vehicle usage, as compared to males. Older individuals were more skeptic about potential benefits of autonomous vehicles, and more concerned about safety issues. Individuals with higher level of education were found to be more in agreement with the potential benefits of autonomous vehicles, and less concerned about safety and security issues. Montoro et al. (2019) surveyed 1,205 drivers from Spain to investigate whether perceived safety benefits of autonomous vehicles have a positive effect towards the intention of using them. One of the findings from this study indicated that tech-savviness of the drivers is correlated to their perceived safety benefits of autonomous vehicles, which, in turn, led to their willingness to use autonomous vehicle technologies once they become available.

1.2. *Motivation of the Present Study*

Autonomous vehicles have the potential to induce a paradigm shift in the ground transportation system. The promises of autonomous vehicles include reduction in crashes and corresponding injuries and fatalities, smoother traveling experience, optimized traffic operations, increase in productivity during commuting, and significant economic and societal benefits resulting from the reduction in crashes and fatalities. However, the success of autonomous vehicles as a game-changing mode of transportation will ultimately depend on the acceptance by the general public, who will be the customer base for this technology. This is true for both personally owned autonomous vehicles, and autonomous vehicles in shared mobility services (e.g., ridesharing, car-sharing). In this context, one of the major contributing factors towards public acceptance is the trust on the autonomous vehicle technologies. Existing studies in the literature focus on measuring public trust based on crucial safety and security related questions. In terms of percentage responses received, these studies showcase the cross-gender, cross-educational, cross-country, and cross-generational differences in public perceptions towards safety and security related questions. However, to better understand how the socio-demographic attributes and driving habits affect individuals' opinions towards safety and security related issues, an in-depth statistical analysis is warranted.

This study seeks to investigate the determinants of public perceptions towards safety benefits, and safety-security related concerns from the use of autonomous vehicles. The data used in this study were obtained from an online survey with the participation of 584 respondents from the United States. It should be noted that the statistical analysis of such survey-obtained data is subjected to significant methodological challenges, most notably due to the almost ubiquitous presence of systematic unobserved variations in the received responses. This phenomenon is also known as unobserved heterogeneity (Mannering and Bhat, 2014; Mannering et al., 2016; Eker et al., 2019; Barbour et al., 2019; 2020; Eker et al., 2020a; 2020b; Ahmed et al., 2020a; 2020b; 2020c; Sheela and Mannering, 2020). To account for the methodological challenges arising from the presence of unobserved heterogeneity, a novel statistical modeling technique, namely the grouped random parameters bivariate probit model with heterogeneity in means is employed. The data collection process, and statistical methodology used in this study are discussed in the next sections.

2. SURVEY AND DATA DESCRIPTION

2.1. Survey Design and Data Collection

To collect perceptual patterns, opinions, and concerns of individuals towards autonomous vehicle technologies, an online survey was conducted in March 2017, using the "SurveyMonkey" platform. To disseminate the survey, 34 students and employees from the University at Buffalo were provided unique survey links, which were then distributed among their peers. In total, 584 individuals from the US responded to the survey. The number of responses received through each unique link varied between 2 and 33.

The survey consisted of three sections. The first section was formulated to explore individuals' perceptions and opinions towards various aspects of autonomous vehicle technologies. Questions focusing on individuals' willingness to pay and willingness to use autonomous vehicles, and their opinions towards perceived benefits and concerns from the use of autonomous vehicles were also included. To measure individuals' knowledge and exposure level to emerging vehicle automation technologies (emergency automatic braking, lane keeping assist, adaptive cruise control, left turn assist, adaptive headlights, and blind-spot monitoring), questions focusing on their level of familiarity, and ownership of vehicles with these technologies were also asked. A four-point Likert Scale was leveraged to record the responses for questions related to the willingness to use, and to perceived benefits and concerns. The options made available to the respondents were: Very unlikely, Somewhat unlikely, Somewhat likely, and Very likely. A similar four-point scale was utilized to measure the respondents' level of familiarity with emerging vehicle automation technologies, with the available options being: Very unfamiliar, Somewhat unfamiliar, Somewhat familiar, and Very familiar.

The second section was aimed to extract information related to individuals' driving habits and history, and their attitudes towards certain driving scenarios. Questions were structured to obtain the respondents' average yearly driving mileage, and accident and traffic violation history. To assess the respondents' propensity towards potential aggressive driving behavior, several questions were also asked (self-assessment of perceived aggressive driving behavior, driving speed in an interstate with 65mph speed limit, attitude towards yellow traffic light in an intersection while driving, opinion towards suggestive speed limits in high speed freeways).

The third (and last) section focused on obtaining the respondents' socio-demographic characteristics (age, gender, marital status, education, living area, and several household-specific characteristics).

2.2. Summary Statistics of Key Variables

Respondents' perceptions towards safety benefits, and safety and security related concerns from the use of autonomous vehicles are summarized in Table 1. The majority of the respondents expected fewer and less severe crashes on the roadway from the use of autonomous vehicles (66.44% and 68.34%, respectively). Although expectations towards safety benefits were significant, safety and security related concerns from the use of autonomous vehicles were even greater. Specifically, 70.76% and 72.84% of the respondents expressed concern towards the possibility of equipment/system failure in adverse weather condition, and towards the possibility of crashes due to equipment/system failure, respectively. Similarly, 67.65% and 73.53% of the respondents were concerned about security threats from hackers and terrorists, and personal information privacy (location and destination monitoring), respectively. Overall, personal information privacy was found to be the most concerning issue among the respondents, closely followed by the concern of equipment/system failure and consequent crash occurrence.

Table 2 presents the descriptive statistics of key variables, those that were found to be statistically significant determinants of the respondents' perceptions towards safety benefits, and safety and security related concerns from the use of autonomous vehicles.

Table 1 Distribution of responses about safety and security related perceptions from the use of autonomous vehicles

	Very unlikely	Somewhat unlikely	**Overall unlikely**	Somewhat likely	Very likely	**Overall likely**
Safety Benefits						
Fewer crashes on the roadway	10.21%	23.36%	**33.56%**	42.04%	24.39%	**66.44%**
Less severe crashes on the roadway	9.69%	21.97%	**31.66%**	42.04%	26.30%	**68.34%**
	Not at all concerned	Slightly concerned	**Overall unconcerned**	Moderately concerned	Very concerned	**Overall concerned**
Safety Concerns						
Equipment/system failure in poor weather (storm, high wind, snow, rain, etc.)	5.36%	23.88%	**29.24%**	47.75%	23.01%	**70.76%**
Crashes due to equipment/system failure	6.40%	20.76%	**27.16%**	45.50%	27.34%	**72.84%**
Security Concerns						
Poor security against hackers and terrorists	7.96%	24.39%	**32.35%**	44.29%	23.36%	**67.65%**
Inadequate personal information privacy (location and destination monitoring)	5.19%	21.28%	**26.47%**	42.04%	31.49%	**73.53%**

Table 2 Descriptive statistics of key variables

Variable Description	Mean	Std. Dev.	Min.	Max.
Socio-demographic Characteristics				
Age indicator (1 if the respondent is younger than 30, 0 otherwise)	0.737	0.441	0	1
Age indicator (1 if the respondent is older than 50, 0 otherwise)	0.132	0.338	0	1
Gender indicator (1 if the respondent is female, 0 otherwise)	0.404	0.491	0	1
Gender indicator (1 if the respondent is male, 0 otherwise)	0.590	0.492	0	1
Marital status indicator (1 if the respondent is single, 0 otherwise)	0.713	0.453	0	1
Education indicator (1 if the respondent has some high school education or a high school diploma, 0 otherwise)	0.257	0.438	0	1
Education indicator (1 if the respondent has a technical college degree or a college degree, 0 otherwise)	0.545	0.498	0	1
Income indicator (1 if the respondent's annual household income is less than $20,000, 0 otherwise)	0.087	0.283	0	1
Income indicator (1 if the respondent's annual household income is between $30,000 and $75,000, 0 otherwise)	0.306	0.461	0	1
Income indicator (1 if the respondent's annual household income is between $30,000 and $100,000, 0 otherwise)	0.464	0.499	0	1
No. of household member indicator (1 if the respondent is from a single person household, 0 otherwise)	0.143	0.351	0	1
Household car ownership indicator (1 if the respondent's household has no car, 0 otherwise)	0.062	0.241	0	1
Household worker count indicator (1 if 2 or more people from the household work outside, 0 otherwise)	0.677	0.468	0	1
Household worker count indicator (1 if 3 or more people from the household work outside, 0 otherwise)	0.348	0.477	0	1
Current living area indicator (1 if the respondent lives in city center, 0 otherwise)	0.102	0.303	0	1
Current living area indicator (1 if the respondent lives in urban area outside city center, 0 otherwise)	0.311	0.463	0	1
Childhood living area indicator (1 if the respondent grew up in suburban area, 0 otherwise)	0.475	0.500	0	1
Opinions and Preferences				
Driving experience indicator (1 if the respondent has a driving license for over 10 years, 0 otherwise)	0.291	0.455	0	1
Driving experience indicator (1 if the respondent has a driving license for over 15 years, 0 otherwise)	0.225	0.418	0	1
Vehicle safety features indicator (1 if the respondent is not familiar with advanced safety features, 0 otherwise)	0.124	0.330	0	1
Vehicle safety features indicator (1 if the respondent never owned a car with an advanced safety feature, 0 otherwise)	0.454	0.498	0	1

Variable Description	Mean	Std. Dev.	Min.	Max.
Traffic violation indicator (1 if the respondent has been pulled over for traffic violation more than 2 times over the last five years, 0 otherwise)	0.267	0.443	0	1
Accident history indicator (1 if the respondent has had no non-severe accidents in the last 5 years, 0 otherwise)	0.697	0.460	0	1
Accident history indicator (1 if the respondent has had more than one non-severe accidents in the last 5 years, 0 otherwise)	0.090	0.286	0	1
Driving speed indicator (1 if the respondent normally drives faster than 65 mph on an interstate with a 65 mph speed limit and little traffic, 0 otherwise)	0.817	0.387	0	1
Speed limit opinion indicator (1 if the respondent is neutral with the statement: "Speed limits on high speed freeways should only be suggestive", 0 otherwise)	0.382	0.486	0	1
Red light reaction indicator(1 if the respondent reacts based on distance to the signal when approaching a traffic signal which is green initially but turns yellow, 0 otherwise)	0.633	0.482	0	1
Mileage indicator (1 if the respondent annually drives less than 300 miles, 0 otherwise)	0.091	0.289	0	1
Mileage indicator (1 if the respondent annually drives less than 650 miles, 0 otherwise)	0.139	0.347	0	1

3. METHODOLOGICAL APPROACH

While the descriptive statistics provided in Table 1 summarize trends in perceptual patterns, the determinants of such patterns cannot be readily drawn from a simple descriptive analysis of the data. To explore and gain better understanding of the determinants of such perceptual patterns, statistical modeling of the safety and security related responses is warranted. The responses presented in Table 1 form the basis of the dependent variables for the subsequent statistical modeling.

The four ordinal options available to respond to the questions related to safety benefits of autonomous vehicles were: Very unlikely, Somewhat unlikely, Somewhat likely, and very likely. To elaborate, the "Very unlikely" and "Somewhat unlikely" options were leveraged to capture the respondents' skepticism towards the potential safety benefits of autonomous vehicles. The choice of any of these two options by the respondents indicates conceptually similar skepticism towards safety benefits of autonomous vehicles. The same explanation is applicable for the "Somewhat likely" and "Very likely" options as well. To capture this effect, "Very unlikely" and "Somewhat unlikely" responses were aggregated to "Overall unlikely". Similarly, "Somewhat likely" and "Very likely" responses were aggregated to "Overall likely". The aggregation resulted in binary response variables, where "Overall likely" is indicated by 1, and "Overall unlikely" is indicated by 0. Following the same framework, the safety and security concern related responses were aggregated to form binary response variables as well. Specifically, "Not at all concerned" and "Slightly concerned" responses were aggregated to "Overall unconcerned", represented by 0; and "Moderately concerned" and "Very concerned" responses were aggregated to "Overall concerned", represented by 1.

3.1. The Bivariate Probit Framework

Given the discrete, binary nature of the aggregated response variables, binary discrete outcome/choice models are well suited for the statistical modeling. However, a closer inspection of the response variables in Table 1 reveals that two safety benefit related responses are: fewer crashes on the roadway, and less severe crashes on the roadway from the use of autonomous vehicles. Since both of these responses capture respondents' perceptions towards conceptually similar crash-related benefits of autonomous vehicles, the determinants of the aforementioned perceptions might be subjected to shared systematic unobserved variations. In statistical terminology, such systematic unobserved variations are captured in the error terms of the dependent variables under consideration. Since both of the aggregated safety benefit related response variables are likely affected by possible shared systematic unobserved variations, the corresponding error terms would be significantly correlated (Russo et al., 2014; Fountas and Anastasopoulos, 2017; Sarwar et al., 2017a; Sarwar et al., 2017b; Bhowmik et al., 2018; Eker et al., 2019; Fountas et al., 2019; Eker et al., 2020a; 2020b; Ahmed et al., 2020a; 2020b; 2020c; Fountas et al., 2020). The safety concern and security concern related responses would be affected by similar systematic unobserved variations as well. To account for the effect of shared systematic unobserved characteristics on conceptually similar binary response variable pairs, the bivariate probit model is employed for statistical modeling. This framework allows simultaneous modeling of two binary dependent variables affected by shared unobserved characteristics, and at the same time, allows accounting for the cross-equation error correlation. The bivariate probit model is defined as follows (Greene, 2017; Sarwar et al., 2017a; Washington et al., 2020),

$$\begin{aligned} Z_{i,1} &= \boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1} + \varepsilon_{i,1}, \quad z_{i,1} = 1 \;\; if \;\; Z_{i,1} > 0, 0 \;\; otherwise \\ Z_{i,2} &= \boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2} + \varepsilon_{i,2}, \quad z_{i,2} = 1 \;\; if \;\; Z_{i,2} > 0, 0 \;\; otherwise \end{aligned} \tag{1}$$

with the error terms defined as,

$$\begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \tag{2}$$

where, **X** is a vector of independent explanatory variables affecting individuals' perceptions towards safety benefits, and safety and security concerns from the use of autonomous vehicles, **β** is a vector of estimable parameters corresponding to **X**, $z_{i,1}$ and $z_{i,2}$ are the binary outcomes of the aggregated dependent variables, $Z_{i,1}$ and $Z_{i,2}$ are corresponding latent variables, ε is a normally distributed error term with mean equal to 0 and variance equal to 1, and ρ is the cross-equation error correlation coefficient. The cumulative bivariate normal probability distribution function, and the associated log-likelihood functions are as follows (Greene, 2017),

$$\Phi\left(Z_1, Z_2, \rho\right) = \frac{\exp\left[-0.5(Z_1^2 + Z_2^2 - 2\rho Z_1 Z_2)/(1-\rho^2)\right]}{\left[2\pi\sqrt{(1-\rho^2)}\right]} \tag{3}$$

and

$$\begin{aligned}\sum_{i=1}^{N}[&z_{i,1}z_{i,2}\ln\Phi(\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},\rho)+(1-z_{i,1})z_{i,2}\ln\Phi(-\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},-\rho)\\ &+(1-z_{i,2})z_{i,1}\ln\Phi(\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},-\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},-\rho)+(1-z_{i,1})(1-z_{i,2})\ln\Phi(-\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},-\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},\rho)]\end{aligned} \tag{4}$$

where, all terms are as previously defined.

3.2. Addressing Unobserved Heterogeneity: Grouped Random Parameters with Heterogeneity in Means Approach

One of the most challenging methodological issues in statistical modeling of survey-collected data is accounting for the unobserved characteristics that may vary systematically across observations or groups of observations. In statistical terms, this is defined as unobserved heterogeneity. In the context of statistically modeling individuals' perceptions towards safety benefit, and safety and security related concerns from the use of autonomous vehicles, the challenge associated with addressing unobserved heterogeneity is even greater. Since autonomous vehicles constitute an emerging form of transportation technology, public perceptions towards this technology can be driven by a plethora of factors. Accurately capturing all causal factors affecting public perceptions towards autonomous vehicles in a survey with limited number of questions is extremely challenging (Becker and Axhausen, 2017). As a consequence, unobserved heterogeneity, if unaccounted for, can result in biased and inconsistent parameter estimates in statistical modeling. This in turn may result in misleading identification of factors and erroneous inference of findings.

To account for the methodological challenge stemming from the presence of unobserved heterogeneity in the survey-collected data, random parameters modeling is employed (Anastasopoulos and Mannering, 2009; Mannering and Bhat, 2014; Anastasopoulos and Mannering, 2016; Greene, 2016; Mannering et al., 2016; Fountas and Anastasopoulos, 2017; Fountas et al., 2018b; Islam and Mannering, 2020; Kabli et al., 2020; Sharma et al., 2020; Washington et al., 2020). When implemented, random parameters allow for the parameter estimates to vary across observational units of the dependent variable(s). In the context of this study, the survey was distributed by 34 individuals among their peers. Hence, presence of shared unobserved characteristics among the responses received by each distributor is highly likely. This is a common phenomenon known as unbalanced panel effects (Sarwar et al., 2017a; Fountas et al., 2018a; Eker et al., 2019; Eker et al., 2020a; 2020b; Ahmed et al., 2020a; 2020b; 2020c). To account for the latter, the parameter estimates are allowed to vary across groups of responses collected by each of the survey distributors. Random parameters are, thus, defined as,

$$\boldsymbol{\beta}_{\mathbf{i}} = \beta + \boldsymbol{\lambda}\mathbf{Y}_{\mathbf{i}} + \delta_{\mathrm{i}}\,. \tag{5}$$

Here, β is the mean of the random parameter, $\mathbf{Y_i}$ is a vector of explanatory variables that influence the mean of $\boldsymbol{\beta}_{\mathbf{i}}$ (Venkataraman et al., 2014; Behnood and Mannering, 2017; Seraneeprakarn et al., 2017; Eker et al., 2019; Islam and Mannering, 2020; Sharma et al., 2020; Pantangi et al., 2020; Hamed and Al-Eideh, 2020), $\boldsymbol{\lambda}$ is a vector of estimable parameters corresponding to $\mathbf{Y_i}$, and $\boldsymbol{\delta}_{\mathbf{i}}$ is a disturbance term with mean equal to zero and variance equal to σ^2. Inclusion of the vector $\mathbf{Y_i}$ is particularly important, because it can capture potential sources of perceptual heterogeneity, as for example, socio-demographics and opinion preferences of the respondents (Washington et al., 2020). Various available parametric distributions were investigated to estimate the grouped random parameters (e.g., normal, triangular, Weibull, log-normal, and uniform), and the normal distribution resulted in the best model specification (in terms of model statistical fit) in all cases.

Pseudo-elasticities of the statistically significant explanatory indicator variables are computed to gain greater insight about the magnitude of their effects on individuals' perceptions towards safety benefit, and safety and security concerns of autonomous vehicles. If an explanatory indicator variable changes from "0" to "1", the associated pseudo-elasticity is computed as follows (Washington et al., 2020),

$$E = \Phi\left(\frac{\beta_j X_{j,1}}{\sigma}\middle| X_i = 1\right) - \Phi\left(\frac{\beta_j X_{j,1}}{\sigma}\middle| X_i = 0\right). \tag{6}$$

The models are developed using a simulated maximum likelihood estimation approach (SMLE) and 600 Halton draws, which were found to provide stable parameter estimates (Bhat, 2003; Train, 2009).

4. MODEL ESTIMATION RESULTS

To explore and identify the factors affecting individuals' perceptions towards safety benefits, and safety and security related concerns, three grouped random parameters bivariate probit models with heterogeneity in means are estimated. The first model explores perceived safety benefits of autonomous vehicles, specifically, fewer crashes and less severe crashes on the roadway. The second model investigates safety concerns, e.g., equipment/system failure in poor weather and crashes due to equipment/system failure, while the third model explores perceptions towards security concerns, e.g., poor security against hackers/terrorists and concern about personal information privacy. In all three models, the cross-equation error correlation terms were found to be above 0.75 and statistically significant, which validates the use of bivariate probit model.

All explanatory variables included in the final model specifications were statistically significant at $\alpha = 0.1$ or lower (confidence level of 0.90 or greater), except for the means of the random parameters. If the mean of a random parameter turned out to be statistically insignificant, and the standard deviation was found to be statistically significant, a chi-square distributed likelihood ratio test with two degrees of freedom was conducted to evaluate the overall model fit. If the test indicated statistically significant improvement in the overall model fit, only then was the random parameter under consideration included in the models.

4.1. Perceptions towards safety benefits from the use of autonomous vehicles

Estimation results and pseudo-elasticities of the model exploring public perceptions towards potential safety benefits (fewer and less severe crashes on the roadway) from the use of autonomous vehicles are presented in Tables 3 and 4, respectively.

Multiple socio-demographic characteristics were found to affect individuals' perceptions towards potential safety benefits from the use of autonomous vehicles. Individuals older than 50 years are less likely to expect fewer and less severe crashes on the roadway (the pseudo-elasticities in Table 4 are -0.264 and -0.131, respectively). The majority of the female respondents (60.94%, per the distributional split of the random parameter density function) are more likely to expect less severe crashes on the roadway (whereas the remaining 39.06% are less likely to do so). Over half (58.83%, per the distributional split of the random parameter density function) of the individuals who have some high school education or a diploma, are less likely to expect fewer crashes on the roadway (whereas the remaining 41.17% is more likely to do so).

Table 3 Estimation results of the grouped random parameters bivariate probit model with heterogeneity in means of safety benefit related perceptions

Variable	Fewer crashes on the roadway		Less severe crashes on the roadway	
	Coeff.	***t*-stat**	**Coeff.**	***t*-stat**
Constant	0.756	4.07	0.843	5.36
Socio-demographic characteristics				
Age indicator (1 if the respondent is older than 50, 0 otherwise)	-0.759	-3.28	-0.511	-2.21
Gender indicator (1 if the respondent is female, 0 otherwise)	–	–	0.163	1.08
Standard deviation of parameter distribution	–	–	*0.587*	*4.94*
Income indicator (1 if the respondent's annual household income is between \$30,000 and \$75,000, 0 otherwise)	–	–	-0.397	-2.75
Income indicator (1 if the respondent's annual household income is between \$30,000 and \$100,000, 0 otherwise)	-0.291	-2.00	–	–
Education indicator (1 if the respondent has some high school education or a high school diploma, 0 otherwise)	-0.106	-0.63	–	–
Standard deviation of parameter distribution	*0.475*	*3.97*	–	–
Household worker count indicator (1 if 2 or more people from the household work outside, 0 otherwise)	0.305	1.36	–	–
Standard deviation of parameter distribution	*0.197*	*2.80*	–	–
Household car ownership indicator (1 if the respondent's household has no car, 0 otherwise)	-0.589	-2.06	-0.659	-2.50
Opinions and preferences				
Vehicle safety features indicator (1 if the respondent never owned a car with an advanced safety feature, 0 otherwise)	–	–	-0.122	-0.86
Standard deviation of parameter distribution	–	–	*0.311*	*3.46*
Accident history indicator (1 if the respondent has had more than one non-severe accidents in the last 5 years, 0 otherwise)	0.456	1.92	–	–
Speed limit opinion indicator (1 if the respondent is neutral with the statement: "Speed limits on high speed freeways should only be suggestive", 0 otherwise)	–	–	0.164	1.03
Standard deviation of parameter distribution	–	–	*0.197*	*2.07*
Heterogeneity in the means				
Household worker count indicator: Marital status indicator (1 if the respondent is single, 0 otherwise)	-0.390	-2.12	–	–
Gender indicator: Current living area indicator (1 if the respondent lives in urban area outside city center, 0 otherwise)	–	–	-0.450	-1.78
Cross equation correlation (*t*-stat in parentheses)	0.819 (18.98)			
Number of survey distributors	34			
Number of respondents	460			
Log-likelihood at convergence	-478.13			
Log-likelihood at zero	-734.95			
Akaike information criterion (AIC)	1000.3			

Distributional splits of the random parameters across the respondents		
	Above Zero	**Below Zero**
Gender indicator (1 if the respondent is female, 0 otherwise)	60.94%	39.06%
Education indicator (1 if the respondent has some high school education or a high school diploma, 0 otherwise)	41.17%	58.83%
Household worker count indicator (1 if 2 or more people from the household work outside, 0 otherwise)	93.92%	6.08%
Vehicle safety features indicator (1 if the respondent never owned a car with an advanced safety feature, 0 otherwise)	34.74%	65.26%
Speed limit opinion indicator (1 if the respondent is neutral with the statement: “Speed limits on high speed freeways should only be suggestive”, 0 otherwise)	79.74%	20.26%

Table 4 (Pseudo-)elasticities of the explanatory variables included in the model of safety benefit related perceptions

Variable	Fewer crashes on the roadway	Less severe crashes on the roadway
Socio-demographic characteristics		
Age indicator (1 if the respondent is older than 50, 0 otherwise)	-0.264	-0.131
Gender indicator (1 if the respondent is female, 0 otherwise)	–	-0.024
Income indicator (1 if the respondent's annual household income is between \$30,000 and \$75,000, 0 otherwise)	–	-0.106
Income indicator (1 if the respondent's annual household income is between \$30,000 and \$100,000, 0 otherwise)	-0.104	–
Education indicator (1 if the respondent has some high school education or a high school diploma, 0 otherwise)	-0.066	–
Household worker count indicator (1 if 2 or more people from the household work outside, 0 otherwise)	-0.006	–
Household car ownership indicator (1 if the respondent's household has no car, 0 otherwise)	-0.213	-0.224
Opinions and preferences		
Vehicle safety features indicator (1 if the respondent never owned a car with an advanced safety feature, 0 otherwise)	–	-0.057
Accident history indicator (1 if the respondent has had more than one non-severe accidents in the last 5 years, 0 otherwise)	0.115	–
Speed limit opinion indicator (1 if the respondent is neutral with the statement: "Speed limits on high speed freeways should only be suggestive", 0 otherwise)	–	0.057

Several household-specific attributes are found to affect individuals' safety benefit related perceptions as well. For instance, individuals from households with annual income between $30K and $100K are less likely to expect fewer crashes on the roadway (the pseudo-elasticity in Table 4 is -0.104). In addition, individuals from households with annual income between $30K and $75K are less likely to expect less severe crashes (by -0.106, as shown by the pseudo-elasticity in Table 4). The vast majority of the respondents (93.92%, per the distributional split of the random parameter density function) from households with multiple residents working outside their home are found to expect fewer crashes on the roadway. In regard to household car ownership, respondents from households without a car are less likely to expect fewer and less severe crashes (by -0.213 and -0.224, respectively, as indicated by the pseudo-elasticities in Table 4).

Lack of ownership of vehicles with advanced safety features is found to have mixed effects on the individuals' expectation for less severe crashes on the roadway. Specifically, nearly two thirds (65.26%, per the distributional split of the random parameter density function) are less likely to expect less severe crashes (whereas the remaining 34.74% are more likely to do so).

Moving to driving history and preferences, individuals who experienced more than one non-severe accidents in the last five years (since the time when they participated in the survey) are more likely to expect fewer crashes on the roadway by 0.115 (as indicated by the pseudo-elasticity in Table 4). The majority of the accidents occur due to (possibly) preventable human errors. The expectation of having fewer crashes by the aforementioned individuals is probably stemming from the autonomous vehicle technologies' potential to remove any human error elements from the accident occurrence mechanism. Furthermore, the majority of individuals (79.74%, per the distributional split of the random parameter density function) who are neutral towards a suggestive role of speed limits in high speed freeways are more likely to expect less severe crashes on the roadway.

Additional insights are offered by two indicator variables that caused significant heterogeneity in means for two random parameters in this model. The marital status indicator (representing single individuals) is found to shift the mean of the random parameter "household worker count indicator" to a lower value. In simpler terms, individuals who are from a household with multiple workers (more than one) and who are also single, are less likely to expect fewer crashes on the roadway, as compared to individuals who are not single. The current living area indicator (representing urban areas, outside the city center) is found to shift the mean of the random parameter "gender indicator (representing female individuals)" to a lower value. This indicates that female respondents who are currently living in urban areas outside city centers are less likely to expect less severe crashes on the roadway, as compared to female respondents currently living elsewhere.

4.2. *Perceptions towards safety concerns from the use of autonomous vehicles*

Tables 5 and 6 present the estimation results and pseudo-elasticities of the model investigating public perceptions towards safety concerns from the use of autonomous vehicles: equipment/system failure in poor weather, and crashes due to equipment/system failure, respectively.

Focusing on socio-demographic determinants of individuals' perceptions towards the safety concerns of autonomous vehicles, individuals from low income households (with annual income less than 20K) are more concerned about both equipment/system failure in poor weather and crashes due to equipment/system failure (by 0.162 and 0.199, respectively, as shown by the pseudo-elasticities in Table 6). Similarly, individuals from households with three or more residents working outside their home are more concerned about equipment/system failure in poor weather and crashes due to equipment/system failure (by 0.126 and 0.153, respectively, as indicated by the pseudo-elasticities in Table 6). The pseudo-elasticities reveal that both of the aforementioned groups are more concerned about crashes due to equipment/system failure than equipment/system failure in poor weather conditions. The underlying reason of the concern towards crashes due to equipment/system failure being more pronounced than that of equipment/system failure in poor weather is probably due to the difference in magnitude of risk perception. In words, the perceived risk associated to crashes is higher in magnitude as compared to the risk of equipment/system failure in poor weather conditions.

The majority of the individuals (85.10%, per the distributional split of the random parameter density function) who are not familiar with advanced vehicle safety features are concerned about crashes due to equipment/system failure. On the contrary, only a small minority (the remaining 14.90%) are not concerned about crashes due to equipment/system failure.

With respect to the driving preferences and history, the model estimation results reveal that individuals who take cautious role and act based on distance while driving towards a traffic signal, which is initially green but turns yellow, are concerned about both equipment/system failure and crashes due to equipment/system failure (by 0.156 and 0.112, respectively, as indicated by the pseudo-elasticities in Table 6). The driving experience of individuals is found to affect their perceptions towards safety concerns from the use of autonomous vehicles as well. The vast majority (83.09%, per the distributional split of the random parameter density function) of individuals who have had a driver’s license for over 10 years (since the survey) are concerned about equipment/system failure in poor weather. In addition, individuals who have had a driver's license for over 15 years (since the survey) are found to be concerned about crashes due to equipment/system failure (by 0.158, as indicated by the pseudo-elasticity in Table 6). These findings are in line with the findings by Schoettle and Sivak (2014).

Two indicator variables are found to result in significant heterogeneity in the means for two random parameters in this model. Specifically, the traffic violation indicator variable (more than two traffic violations over the last five years) resulted in shifting the mean of the random parameter "driving experience indicator" (individuals who have had a driving license for over 10 years), to a lower magnitude. This finding indicates that experienced drivers (with more than 10 years of driving experience, since the survey) who are also somewhat aggressive in their driving behavior (in terms of number of pull overs over the last five years) are less likely to be concerned about equipment/system failure in poor weather, as compared to their less aggressive counterparts. In addition, the current living area indicator (city center) variable was found to shift the mean of the random parameter "vehicle safety feature indicator" to a smaller magnitude. This reveals that city center dwellers who are not familiar with advanced safety features are less likely to be concerned about crashes due to equipment/system failure, as compared to their non-city center dweller counterparts.

Table 5 Estimation results of the grouped random parameters bivariate probit model with heterogeneity in means of safety concern related perceptions

Variable	Equipment/system failure in poor weather (storm, high wind, snow, rain, etc.)		Crashes due to equipment/system failure	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**
Socio-demographic characteristics				
Income indicator (1 if the respondent's annual household income is less than $20,000, 0 otherwise)	0.600	2.49	0.703	1.93
Household worker count indicator (1 if 3 or more people from the household work outside, 0 otherwise)	0.362	2.88	0.464	3.62
Opinions and preferences				
Vehicle safety features indicator (1 if the respondent is not familiar with advanced safety features, 0 otherwise)	–	–	0.408	1.61
Standard deviation of parameter distribution	–	–	*0.392*	*1.80*
Red light reaction indicator(1 if the respondent reacts based on distance to the signal when approaching a traffic signal which is green initially but turns yellow, 0 otherwise)	0.422	4.16	0.338	3.28
Driving experience indicator (1 if the respondent has a driving license for over 10 years, 0 otherwise)	0.203	1.30	–	–
Standard deviation of parameter distribution	*0.212*	*2.54*	–	–
Driving experience indicator (1 if the respondent has a driving license for over 15 years, 0 otherwise)	–	–	0.530	3.28
Heterogeneity in the means				
Driving experience indicator: Traffic violation indicator (1 if the respondent has been pulled over for traffic violation more than 2 times over the last five years, 0 otherwise)	-0.471	-1.68	–	–
Vehicle safety features indicator: Current living area indicator (1 if the respondent lives in city center, 0 otherwise)	–	–	-1.528	-2.32
Cross equation correlation (t-stat in parentheses)	0.761 (12.89)			
Number of survey distributors	34			
Number of respondents	464			
Log-likelihood at convergence	-479.19			
Log-likelihood at zero	-687.94			
Akaike information criterion (AIC)	986.4			
Distributional splits of the random parameters across the respondents				
	Above Zero		**Below Zero**	
Vehicle safety features indicator (1 if the respondent is not familiar with advanced safety features, 0 otherwise)	85.10%		14.90%	
Driving experience indicator (1 if the respondent has a driving license for over 10 years, 0 otherwise)	83.09%		16.91%	

Table 6 (Pseudo-)elasticities of the explanatory variables included in the model of safety concern related perceptions

Variable	Equipment/system failure in poor weather (storm, high wind, snow, rain, etc.)	Crashes due to equipment/system failure
Socio-demographic characteristics		
Income indicator (1 if the respondent's annual household income is less than $20,000, 0 otherwise)	0.162	0.199
Household worker count indicator (1 if 3 or more people from the household work outside, 0 otherwise)	0.126	0.153
Opinions and preferences		
Vehicle safety features indicator (1 if the respondent is not familiar with advanced safety features, 0 otherwise)	–	0.037
Red light reaction indicator(1 if the respondent reacts based on distance to the signal when approaching a traffic signal which is green initially but turns yellow, 0 otherwise)	0.156	0.112
Driving experience indicator (1 if the respondent has a driving license for over 10 years, 0 otherwise)	0.051	–
Driving experience indicator (1 if the respondent has a driving license for over 15 years, 0 otherwise)	–	0.158

4.3. Perceptions towards security concerns from the use of autonomous vehicles

The estimation results and pseudo-elasticities of the models investigating individuals' perceptions towards security concerns from the use of autonomous vehicles (poor security against hackers/terrorists, and inadequate personal information privacy due to location/destination monitoring) are presented in Tables 7 and 8, respectively.

Several socio-demographic attributes are found to affect the respondents' perceptions towards security concerns from the use of autonomous vehicles. Over two thirds (77.63%, per the distributional split of the random parameter density function) of the individuals having a college or technical college degree are not concerned about personal information privacy issues in the form of location/destination monitoring. This finding is in line with the findings from Cunningham et al. (2019). Almost all of the individuals (99.31%, per the distributional split of the random parameter density function) who are living in urban areas outside city centers are concerned about security threats posed by hackers or terrorists. On the contrary, individuals who grew up in suburban areas are less concerned about personal information privacy issue (by -0.105, as shown by the pseudo-elasticity in Table 8). The majority of individuals from single person households are concerned about security threats from hackers or terrorists, and personal information privacy issue (95.14% and 89.22%, respectively, per the distributional split of the random parameter density function). Similarly, nearly three quarters of the respondents (74.50%, per the distributional split of the random parameter density function) who are not familiar with advanced vehicle safety features are concerned with security threats posed by hackers or terrorists.

Table 7 Estimation results of the grouped random parameters bivariate probit model with heterogeneity in means of security concern related perceptions

Variable	Poor security against hackers/terrorists		Inadequate personal information privacy (location/destination monitoring)	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**
Constant	0.403	3.74	1.212	5.54
Socio-demographic characteristics				
Education indicator (1 if the respondent has a technical college degree or a college degree, 0 otherwise)	–	–	-0.117	-0.73
Standard deviation of parameter distribution	–	–	*0.154*	*1.90*
Current living area indicator (1 if the respondent lives in urban area outside city center, 0 otherwise)	0.527	1.98	–	–
Standard deviation of parameter distribution	*0.214*	*1.81*	–	–
Childhood living area indicator (1 if the respondent grew up in suburban area, 0 otherwise)	–	–	-0.317	-2.36
No. of household member indicator (1 if the respondent is from a single person household, 0 otherwise)	0.982	2.27	0.976	1.97
Standard deviation of parameter distribution	*0.592*	*2.50*	*0.788*	*3.15*
Opinions and preferences				
Vehicle safety features indicator (1 if the respondent is not familiar with advanced safety features, 0 otherwise)	0.365	1.64	–	–
Standard deviation of parameter distribution	*0.554*	*2.71*	–	–
Accident history indicator (1 if the respondent has had no non-severe accidents in the last 5 years, 0 otherwise)	–	–	-0.357	-2.22
Accident history indicator (1 if the respondent has had more than one non-severe accidents in the last 5 years, 0 otherwise)	0.583	1.73	–	–
Mileage indicator (1 if the respondent annually drives less than 300 miles, 0 otherwise)	–	–	-0.666	-2.05
Mileage indicator (1 if the respondent annually drives less than 650 miles, 0 otherwise)	-0.003	-0.01	–	–
Standard deviation of parameter distribution	*0.678*	*3.00*	–	–
Heterogeneity in the means				
Mileage indicator: Gender indicator (1 if the respondent is male, 0 otherwise)	-0.835	-1.95	–	–
Current living area indicator: Age indicator (1 if the respondent is younger than 30, 0 otherwise)	-0.575	-1.98	–	–
No. of household member indicator: Driving speed indicator (1 if the respondent normally drives faster than 65 mph on an interstate with a 65 mph speed limit and little traffic, 0 otherwise)	-0.909	-1.94	–	–
No. of household member indicator: Age indicator (1 if the respondent is younger than 30, 0 otherwise)	–	–	-1.190	-2.26
Cross equation correlation (t-stat in parentheses)	0.802 (12.04)			
Number of survey distributors	34			

Number of respondents	443	
Log-likelihood at convergence	-445.98	
Log-likelihood at zero	-698.59	
Akaike information criterion (AIC)	938	
Distributional splits of the random parameters across the respondents		
	Above Zero	**Below Zero**
Education indicator (1 if the respondent has a technical college degree or a college degree, 0 otherwise)	22.37%	77.63%
Current living area indicator (1 if the respondent lives in urban area outside city center, 0 otherwise)	99.31%	0.69%
No. of household member indicator (1 if the respondent is from a single person household, 0 otherwise) [Poor security against hackers/terrorists]	95.14%	4.86%
No. of household member indicator (1 if the respondent is from a single person household, 0 otherwise) [Inadequate personal information privacy]	89.22%	10.78%
Vehicle safety features indicator (1 if the respondent is not familiar with advanced safety features, 0 otherwise)	74.50%	25.50%
Mileage indicator (1 if the respondent annually drives less than 650 miles, 0 otherwise)	49.82%	50.18%

Table 8 (Pseudo-)elasticities of the explanatory variables included in the model of security concern related perceptions

Variable	Poor security against hackers/terrorists	Inadequate personal information privacy (location/destination monitoring)
Socio-demographic characteristics		
Education indicator (1 if the respondent has a technical college degree or a college degree, 0 otherwise)	–	-0.084
Current living area indicator (1 if the respondent lives in urban area outside city center, 0 otherwise)	0.051	–
Childhood living area indicator (1 if the respondent grew up in suburban area, 0 otherwise)	–	-0.105
No. of household member indicator (1 if the respondent is from a single person household, 0 otherwise)	0.085	0.030
Opinions and preferences		
Vehicle safety features indicator (1 if the respondent is not familiar with advanced safety features, 0 otherwise)	0.133	–
Accident history indicator (1 if the respondent has had no non-severe accidents in the last 5 years, 0 otherwise)		-0.099
Accident history indicator (1 if the respondent has had more than one non-severe accidents in the last 5 years, 0 otherwise)	0.173	–
Mileage indicator (1 if the respondent annually drives less than 300 miles, 0 otherwise)	–	-0.205
Mileage indicator (1 if the respondent annually drives less than 650 miles, 0 otherwise)	-0.169	–

Table 9 Goodness-of-fit measures

	Safety benefit related perceptions				**Safety concern related perceptions**				**Security concern related perceptions**			
	FP[a]	RP[b]	GRP[c]	GRPHM[d]	FP[a]	RP[b]	GRP[c]	GRPHM	FP[a]	RP[b]	GRP[c]	GRPHM[d]
Number of estimated parameters	15	20	20	22	10	12	12	14	13	19	19	23
Log-likelihood at convergence	-490.47	-486.96	-480.78	-478.13	-494.06	-493.51	-492.33	-479.19	-464.55	-463.7	-460.02	-445.98
Log-likelihood at zero	-734.95	-734.95	-734.95	-734.95	-687.94	-687.94	-687.94	-687.94	-698.59	-698.59	-698.59	-698.59
McFadden pseudo-ρ^2	0.333	0.337	0.346	0.349	0.282	0.283	0.284	0.303	0.335	0.336	0.342	0.362
McFadden adjusted pseudo-ρ^2	0.312	0.310	0.319	0.320	0.267	0.265	0.267	0.283	0.316	0.309	0.314	0.329
Akaike information criterion (AIC)	1011.0	1013.9	1001.6	1000.3	1008.1	1011.0	1008.7	986.4	955.1	965.4	958.0	938.0

[a] FP – Fixed parameters bivariate probit model
[b] RP – Random parameters bivariate probit model
[c] GRP – Grouped random parameters bivariate probit model
[d] GRPHM – Grouped random parameters bivariate probit model with heterogeneity in means

Multiple driving history related indicators are also found to affect individuals' perceptions towards security concerns from the use of autonomous vehicles. Individuals who did not experience any non-severe accidents in the last five years (since the survey) are not concerned about personal information privacy issue (by -0.099, as indicated by the pseudo-elasticity in Table 8). Individuals who had more than one non-severe accidents in the last five years (since the survey) are concerned about security threats posed by hackers or terrorists (by 0.173, as shown by the pseudo-elasticity in Table 8). With regard to the average annual driving mileage, individuals with very low annual driving mileage (below 300 miles a year) are found not to be concerned about personal information privacy. However, individuals who drive less than 650 miles are found to have mixed opinion towards security threats from hacker or terrorist attacks. Specifically, 49.82% (per the distributional split of the random parameter density function) of the respondents from the latter group are concerned, whereas the remaining 50.18% are found not to be concerned.

Four indicator variables are found to result in significant heterogeneity in the means for four of the random parameters in the security concern related model. The gender indicator variable (representing male individuals) is found to negatively affect the mean of the mileage indicator variable (reflecting annual driving mileage less than 650 miles). In simpler terms, male individuals among respondents who drive less than 650 miles a year are less likely to be concerned about security threats due to hacker or terrorist attacks. The age indicator variable (representing individuals younger than 30 years old) is found to negatively affect the mean of the current living area indicator variable (representing urban areas outside city centers). This means that individuals younger than 30 years old and who are currently living in urban areas outside city centers are less likely to be concerned about security threats due to hacker or terrorist attacks. The estimation results also indicate that individuals from single person households, who also drive at a speed greater than 65 mph in an interstate with 65 mph speed limit, are less likely to be concerned about security threats due to hacker and terrorist attacks. Finally, individuals younger than 30 years old, who are also from single person households, are less likely to be concerned about personal information privacy issue due to location or destination monitoring.

4.4. *Model evaluation*

Table 9 presents the goodness-of-fit measures of the estimated grouped random parameters bivariate probit models with heterogeneity in means, along with their counterparts. As indicated by the McFadden pseudo- ρ^2, adjusted McFadden pseudo- ρ^2, and the Akaike Information Criterion (AIC), the grouped random parameters bivariate probit models with heterogeneity in means provide the best overall statistical fit compared to its fixed parameters, random parameters, and grouped random parameters bivariate probit counterparts. Specifically, the overall gain in statistical fit offered by the heterogeneity in means approach indicates the strong presence of individual heterogeneity in the survey collected responses used in this study.

5. PRACTICAL IMPLICATIONS

The findings from the present study are anticipated to enable autonomous vehicle stakeholders (government and local authorities, manufacturers, mobility service providers and transportation planners) to initiate safe and successful deployment of autonomous vehicles for the transportation network users.

The perceptual determinants of safety and security related concerns in the US from the use of autonomous vehicles, are indicators of key issues that constitute adoption barriers of autonomous vehicles. The individual-specific characteristics and attributes identified in this study direct towards specific sub-groups of the population who hold significant skepticism towards autonomous vehicle technologies. Governmental organizations (i.e., regulatory and legislative authorities) can proceed towards formulation and incremental revision of policy frameworks to address safety and security related concerns in the US towards autonomous vehicles. As far as the autonomous vehicle manufacturers and autonomous vehicle-based ridesharing and carsharing service providers are concerned, both can address the particular safety and security related concerns in their products, and reach out to the users with targeted information spreading campaigns. It should be noted that the information spreading campaigns should be fine-tuned for different sub-groups of the population to achieve maximum dissemination of assuring information regarding autonomous vehicles. Such initiatives and campaigns have the potential to alleviate concerns of potential users of autonomous vehicles. For example, individuals who are older than 50 years, who do not hold a college degree, who are from household without cars are found to be skeptical towards potential safety benefits of autonomous vehicles. Information spreading campaigns targeted towards the aforementioned sub-groups of the population can be initiated by autonomous vehicle manufacturers and mobility service providers. Such campaigns may contain information showcasing comparative safety advantages of autonomous vehicles (in terms of non-fatal and fatal crashes per million vehicle miles traveled) over non-autonomous vehicles. Similar approaches can be taken towards sub-groups of the populations who are found to be concerned towards the operational reliability and security of autonomous vehicles. Moreover, collaborative effort between the industry and governmental organizations to alleviate safety and security related concerns towards autonomous vehicles may hold the potential to be more impactful.

6. DIRECTIONS TOWARDS FUTURE RESEARCH

This study is conducted using data collected from a cross-sectional online survey. The survey was distributed by 34 students and employees from the University at Buffalo among their acquaintances. The sample used in the study consists of 59% male respondents, as compared to 49.2%, which is the proportion of males in the US population. In addition, 74.38% of the respondents who participated in the survey have at least a college degree, as compared to 30.9% nationally in the US. In terms of educational attainment level, the sample is skewed towards highly educated sub-groups of the population. Additionally, due to the nature of the survey distribution approach, the collected sample poses several methodological challenges. To that end, the novel statistical methodology utilized in this study has effectively accounted for the aforementioned issues. The use of random parameters to successfully account for sampling bias is well-documented in the literature (Anastasopoulos and Mannering, 2009; Anastasopoulos et al., 2012; Mannering et al., 2016; Sarwar et al., 2017a; Pantangi et al., 2019; Pantangi et al., 2020; Sheela and Mannering, 2020; Washington et al., 2020).

Technological advancements in autonomous vehicle design and manufacturing are taking place at a rapid pace. Additionally, autonomous vehicle related news are spreading through multiple easily accessible platforms (online newsrooms, social media, etc.). Exposure to such new information relating to autonomous vehicles is likely to bring forth a transition in the public's perceptions. In this context, an inherent limitation of cross-sectional surveys is the difficulty to capture the change in public perceptions and mobility-related behavioral shifts taking place over time. To that end, future research on this topic can focus on leveraging the traditional longitudinal data collection approach. Another potential approach would be utilizing multiple cross-sectional samples collected by the same survey questionnaire, and investigating temporal transferability of perceptual determinants, by implementing cutting-edge tests of statistical transferability (Mannering, 2018).

7. SUMMARY AND CONCLUSION

To explore perceptions towards autonomous vehicle technologies, responses from 584 individuals in the US were collected through an online survey. The results obtained from the survey offered different aspects of public expectations and concerns from the use of autonomous vehicles. From the use of autonomous vehicles, fewer and less severe crashes are expected by 66% and 68% respondents, respectively. Despite expecting a reduction in the number of crashes and in the injury-severity level, the respondents expressed their concern towards safety and security related issues that may arise from the use of autonomous vehicles. Concern over equipment/system failure in poor weather, and crashes due to equipment/system failure were expressed by 71% and 73% of the respondents, respectively. In addition, security threats due to hacker or terrorist attacks, and personal information privacy issues (in the form of location or destination monitoring) were also identified as sources of concern by 68% and 74% of the respondents, respectively.

To investigate the determinants of the aforementioned safety benefits and safety-security related concerns, a novel statistical modeling technique, namely the grouped random parameters bivariate probit model with heterogeneity in means, is employed in this study. In total, three models were estimated. The estimation results offered significant insights about the perceptual determinants. For example, elderly individuals, individuals from households without cars, and individuals from mid-income households, are not expecting fewer and less severe crashes on the roadway from the use of autonomous vehicles. Individuals from lower income households, and from households with three or more residents working outside their home, are concerned with equipment/system failure in poor weather, as well as crashes due to equipment/system failure. Individuals with 10 years or greater driving experience are also concerned with the aforementioned safety issues from the use of autonomous vehicles. The vast majority of individuals from single person households are concerned with security threats due to hacker or terrorist attacks, and personal information privacy (in the form of location or destination monitoring). Finally, individuals currently living in urban areas (outside city centers), and individuals who experienced more than one non-severe accident over the last five years (since the survey) are concerned with security threats due to hacker or terrorist attacks. Heterogeneous perceptual patterns captured by the grouped random parameters are explained in greater detail by the indicator variables that resulted in heterogeneity in means.

The investigation of public perceptions towards autonomous vehicles should be a continuous endeavor. Exposure to new information regarding autonomous vehicle technologies and pilot launches of relevant mobility services through various means, can result in rapid transformations of the public perceptions towards the use and adoption of autonomous vehicles. Continuous assessment of public perceptions and their transformation over time, and evaluation of the determinants of such changes, are key to the successful deployment of autonomous vehicles. In this context, the findings from this study are anticipated to form a reference point for future studies of similar nature.

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