Investigating safety and liability of autonomous vehicles: Bayesian random parameter ordered probit model analysis

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Abstract

Purpose – This study aims to investigate the safety and liability of autonomous vehicles (AVs), and identify the contributing factors quantitatively so as to provide potential insights on safety and liability of AVs.

Design/methodology/approach – The actual crash data were obtained from California DMV and Sohu websites involved in collisions of AVs from 2015 to 2021 with 210 observations. The Bayesian random parameter ordered probit model was proposed to reflect the safety and liability of AVs, respectively, as well as accommodating the heterogeneity issue simultaneously.

Findings – The findings show that day, location and crash type were significant factors of injury severity while location and crash reason were significant influencing the liability.

Originality/value – The results provide meaningful countermeasures to support the policymakers or practitioners making strategies or regulations about AV safety and liability.

Keywords Safety, Bayesian random parameter ordered probit model, Liability, Autonomous vehicles, Advanced vehicle safety systems

Paper type Research paper

1. Introduction

With the rapid progression of artificial intelligence and communication technology, autonomous vehicle (AV) has been developing and testing by a great number of countries, regions, international automakers and the new internet companies like a swarm of bees. Indeed, the utilization of AVs will bring a series of advantages, e.g. alleviating the traffic congestion, reducing traffic crashes and fatalities (Sparrow and Howard, 2017; Martinho *et al.*, 2021) and mitigating the environmental burden. However, in spring 2018 the first pedestrian fatality caused by Uber driverless vehicle in Tempe, AZ, was paid attention globally, and the doubt whether the driverless cars are safe and who is responsible for the fault has aroused again.

Shown from this event, two critical issues can be extracted, safety and liability. When traffic crashes or fatalities occur, it is necessary to investigate how to determine the injury severity levels, and who is responsible for the crash, the AV itself, the owner or the administration department [More details can be referred to Li *et al.* (2022)]. Nowadays, the AVs' R&D and on-site testing have been growing vigorously all over the world, and the commercialization will be realized in the near future. Faced with the pressing situation, it is of significance to tackle the safety and liability of AVs so as to propose some new thoughts and solutions.

However, current studies about AVs' safety and liability are mainly focused on the qualitative discussion of safety, liability, privacy and ethics from the perspective of social science whereas

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there is not much quantitative analysis on the actual crashes of AVs. Therefore, the purpose of this work is to investigate the safety and liability of AVs with actual crashes and provide potential insights on safety and liability so that corresponding countermeasures can be taken before the commercialization of AVs.

2. Literature review

Currently, most studies about crashes are more concerned with the human-driven vehicles, while fewer studies are focused on crashes of AVs, but there are some attempts from different perspectives.

"Safety First" is still the utmost issue to be investigated in AVs. Moody *et al.* (2020) used multilevel structural equation model to investigate differences in perceptions of AV safety in different countries. At the individual level and country level, and developed and developing countries, different influencing factors were identified, but the common view were reached on the safety AVs adequately to be used. Wang *et al.* (2020) summarized the safety-related issues for AVs and provided the descriptive statistics analysis of accidents for on-road testing, which described the accidents quantitatively and the AV system architecture macroscopically, and can be considered as the fundamentals of our study. From the perspective of experienced industry professionals, Rezaei and Caulfield (2021) collected the comments and suggestions on AVs' safety benefits and drawbacks. Although the severity may keep unchanged or even more severe, the majority of the professionals reached the conclusion that AVs can increase the road safety significantly.

In recent years, actual crashes of CAVs have been attempted to improve the safety. Xu *et al.* (2019) investigated the characteristics of CAV involved crashes in California with bootstrap based binary logistic regressions. It was found that CAV driving mode was significant influencing factor for collision type and severity level of CAV involved crashes. Liu *et al.* (2021) compared the AV crashes and conventional vehicle crashes and found the two groups differed in the proportion of crashes. An in-depth investigation revealed that perception-reaction time, inaccurate identification and insufficient path planning were significant causes of AV crashes. Similarly, Song *et al.* (2021) displayed that the most representative pattern in AV crashes was "collision following AV stop", and Ye *et al.* (2021) estimated traffic injuries involving AVs, which showed that autonomous mode can't perform better in road traffic safety. From the perspective of vulnerable road users (VRUs), Kutela *et al.* (2022) explored patterns of AV crashes and it was found that crosswalks, intersections, traffic signals and movements of AVs were critical for VRUs-AV related crashes.

Besides safety, the related issues have been discussed. Dhar (2016) discussed the equity, safety and privacy in the autonomous vehicle era. Taeihagh and Lim (2019) provided emerging responses for safety, liability, privacy, cybersecurity and industry risks of AVs. It was stated that legislations about privacy and cybersecurity by the USA, laws about liability issues by the UK and Germany, and other countries had acknowledged the relevant issues, and more attention should be paid to environmental and employment risks. Di *et al.* (2020) investigated the road safety affected by AVs and compared the liability rules of AVs and human drivers. A hierarchical game was proposed, including a Stackelberg game between the AV manufacturer and human vehicles, and between lawmakers and other users. Numerical analysis was simulated to determine the AV manufacturer's role in safety and lawmaker's role in liability design. Martinho *et al.* (2021) discussed the ethical issues by the AV industry and provided seven suggestions, in which AVs would not get rid of accidents, and liability risk relied on rules and regulations, and even crash avoidance algorithms. Similarly, Lundgren (2021) discussed what mattered most for policies on AVs: safety requirements vs. crashing ethically. Yuan (2021) studied a framework and method to investigate the accidents involving intelligent vehicles, which provide relevant reference for the analysis on AVs' crashes.

Bayesian random parameter model has been widely applied in crash injury severity analysis of traditional human-driven vehicles, in which Bayesian multilevel/hierarchical random parameter models (Castro and Kim, 2016; Alarifi *et al.*, 2017; Han *et al.*, 2018; Li *et al.*, 2019; Fu and Sayed, 2021) were developed to address the unobserved heterogeneity issue by allowing parameters of risk factors to vary randomly, while Bayesian multivariate random parameter models with spatio-temporal regression (Guo *et al.*, 2019; Zeng *et al.*, 2019; Huang *et al.*, 2019; Wei *et al.*, 2021) were proposed to accommodate the unobserved heterogeneity issue as well as spatial correlation. All of these provide the foundation for the crash analysis of AVs.

In summary, crash analysis in intelligent transportation systems, especially in the connected and autonomous vehicles environment, is critical for the safety improvement. As stated above, most of studies are focused on the qualitative analysis of AVs' safety, whereas a few work is concentrated on the actual crash analysis of AVs. Therefore, the purpose of this study is to investigate the crash analysis and liability of AVs with the real AV crashes collected, and find out the influencing factors with random parameter model.

3. Methodology

In accordance with the literature review above, so far there have been various methods and approaches for injury severity evaluation and prediction, but currently random parameter probit model has been widely accepted. Hence based on the injury features of AVs, the severity levels are modeled as ordinal (i.e. no injury, slight injury, severe injury, fatality), and Bayesian random parameter ordered probit model is considered to evaluate the injury severity, as well as liability.

Taken the injury severity as example and followed the ordinal feature of injury severity, ordered probit model can be expressed as:

$$Y_i^* = \beta_i X_i + \varepsilon_i \tag{1}$$

where X_i is the vector of explanatory variables, β_i denotes the vector of estimated parameters, ε_i is the error term, which is assumed to be normally distributed (zero mean and unit variance) with cumulative distribution denoted by $\Phi(\cdot)$. The injury severity Y_i^* for observation i is described as:

$$Y_i^* = j, \quad \text{if } u_{i,j-1} \le Y_i^* \le u_{i,j} \tag{2}$$

where j (j = 0,1,2…,J) represents the injury-severity level, $u_{i,j}$ is estimated thresholds, and $u_{i,0} = -\infty$ and $u_{i,J} = +\infty$. The thresholds values can distinguish the various injury severity categories, and the injury severity levels j = 0, 1, 2, 3, 4, 5, respectively, for vehicle slight, vehicle severe, no injury, slight injury, severe injury and fatality.

The probability of an observation i being jth injury severity can be expressed as:

$$\begin{aligned} P(y=0) &= \Phi(-\beta_i X_i) \\ P(y=1) &= \Phi(u_1-\beta_i X_i) - \Phi(-\beta_i X_i) \\ P(y=2) &= 1-\Phi(u_1-\beta_i X_i) \end{aligned} \tag{3}$$

where P(y = j) is the probability of the jth injury severity level.

To allow for the effect of the variables to vary across observations and to capture the unobserved heterogeneity in the data, random parameters are considered, and can be incorporated in the ordered probit model by considering:

$$\beta_i = \beta + \mu_i \tag{4}$$

where μ_i is a random distributed term.

In this study, Bayesian estimation approach is employed for the random parameter ordered probit model due to the following advantages over other methods (Yuan *et al.*, 2020): First, the uncertainty is considered in estimating parameters by simulating posterior distribution; second, it is valid in small samples, compared with the asymptotic maximum likelihood method. In maximum likelihood estimation, the true value of the model parameters are considered as fixed but unknown. It maximizes the likelihood of an unknown parameter θ when given the observed data y through the relationship $L(\theta|y) \propto p(y|\theta)$, whereas Bayesian estimation approximates the posterior density of y, $p(\theta|y) \propto p(\theta)\ L(\theta|y)$ where $p(\theta)$ is the prior distribution of θ and $p(\theta|y)$ is the posterior density of θ given y. Therefore, the posterior density of y given θ is the product of the prior distribution of θ and the likelihood of the observed data as follows:

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{\int p(y|\theta)p(\theta)d\theta} \propto p(\theta)L(\theta|y) \tag{5}$$

In this study, non-information priori is adopted because prior information does not exist, while a new class of simulation techniques named Markov Chain Monte Carlo is implemented to compute the joint posterior distribution. For model comparison, as provided by many other studies (Xu *et al.*, 2016, 2020) under the Bayesian framework, the deviance information criterion (DIC) is used to compare the corresponding models abovementioned:

$$DIC = D(\overline{\theta}) + 2p_D = \overline{D} + p_D \tag{6}$$

where $D(\overline{\theta})$ is the deviance evaluated at $\overline{\theta}$, the posterior mean of the parameter of interest, p_D is the effective number of parameter in the model, and $\overline{D}$ is the posterior mean of the deviance statistic $D(\overline{\theta})$. The lower the DIC, the better the model fits. Generally speaking, differences in DIC of more than 10 definitely rule out the model with the higher DIC; differences between 5 and 10 are considered substantial, while the difference less than 5 indicates that the models are not statistically different.

4. Data description

As stated above, the actual crash data of AVs were obtained from California DMV and Sohu websites involved in collisions of AVs with 2015–2021, and 210 crashes were the target population selected in this study from different companies, including Google, Tesla, GM, Alphabet and Ford. These crashes are classified and simulated by Pc-crash software system. Figure 1 shows the typical crash scenarios involving AVs.

Four main aspects of crashes were collected and considered as dependent and independent variables: injury and liability profiles, AV features and the environment conditions.

As stated in the title, the dependent variables here include safety and liability. According to the injury classification, the severity levels include no injury, vehicle slight (vehicle injured slightly), vehicle severe (vehicle injured severely), slight injury (person involved), severe injury (person involved) and fatality, while the responsibility relies on AV system, AV driver, 2nd party and 3rd party (i.e. roadway, environment and other factors besides the AV and drivers). Although there does not exist intrinsic order in responsibility, here to explain the dependent variable, ordinal form is considered correspondingly for both in the form of categories.

Accompanied with the severity levels, injury time, day, location, crash type and crash reason (e.g. malfunction, AV driver wrong operation, 2nd party driver wrong operation) are also collected; the AV-related variable mainly depends on vehicle action (e.g. still, reverse, right-turn or left-turn, straightforward) and intelligence level; the environment conditions include the weather and lighting conditions.

To evaluate the proposed models, the categorical parameters are digitalized and listed in Table 1.

5. Results

Based on the variables selected from the four aspects, the correlation among independent variables needs to be examined before running the model. The Pearson correlation test was conducted to avoid the co-linearity. Shown from the test result, none of the variables selected are highly related.

To make the comparison, Bayesian pooled ordered probit and random parameter ordered probit model are conducted to evaluate the injury severity and liability correspondingly. Meanwhile, to examine whether there exists endogeneity

Figure 1 AV crash types

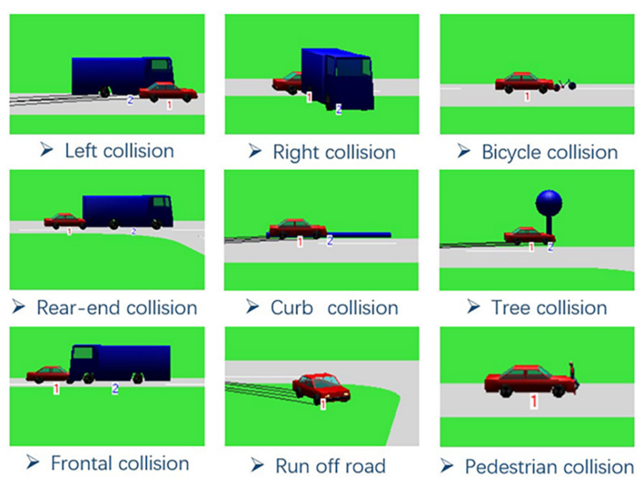


Table 1 Summary of the variables

Variable	Description		Proportion (%)
Dependent variable			
Severity	No injury	0	9(4.3)
	Vehicle slight	1	165(78.5)
	Vehicle severe	2	6(2.9)
	Slight injury	3	6(2.9)
	Severe injury	4	4(1.9)
	Fatality	5	20(9.5)
Liability	AV system	0	5(2.4)
	AV driver	1	145(69.0)
	2nd party	2	33(15.7)
	3rd party	3	27(12.9)
Independent variable			
Time	Off-peak	0	170(80.9)
	Peak	1	40(19.1)
Day	Day	0	162(77.1)
	Night	1	48(22.9)
Location	Intersection	0	140(66.7)
	Segment	1	70(33.3)
Crash type	Frontal	0	33(15.7)
	Rear-end	1	148(70.5)
	Right collision	2	13(6.2)
	Left collision	3	16(7.6)
Crash reason	Malfunction	0	7(3.3)
	AV driver wrong operation	1	147(70.0)
	2nd party driver wrong operation	2	50(23.8)
	Non-motorized vehicles	3	6(2.9)
Intelligence level	Level 2	0	3 (1.4)
	Level 3	1	32(15.2)
	Level 4	2	168(80.0)
	Level 5	3	7(3.3)
Vehicle action	Still	0	16(7.6)
	Reverse	1	5(2.4)
	Right-turn	2	122(58.1)
	Left-turn	3	10(4.8)
	Straightforward	4	57(37.1)
Weather	Unknown	0	5(2.3)
	Sunny	1	195(92.9)
	Cloudy	2	4(1.9)
	Rainy	3	6(2.9)
Light	Unknown	0	6(2.9)
	Sunlight	1	174(82.9)
	Street light	2	30(14.2)
AV brand	Alphabet	1	31(31.96)
	Tesla	2	24 (24.74)
	GM	3	22(22.68)
	Others	0	20(20.62)

between injury severity and liability, simultaneous equation model is performed, which reveals that there is no endogenous relation between them, hence the two models are conducted separately. Tables 2 and 3 give the final results of four models.

Shown from Tables 2 and 3, some observations can be sorted out. First, the significant variables of Bayesian pooled ordered probit and Bayesian random parameter ordered probit models are identical, but the pooled ordered probit model has one significant variable shortage. Second, the DIC values (260.424 and 272.454) from proposed model are smaller than those (272.209 and 273.763) from pooled ordered probit models, respectively, but the difference in Table 2 is beyond 10, which indicates the models are statistically different, while the values of liability in Table 3 are very close to each other, implying that there is not much difference between Bayesian pooled and random parameter models. Generally speaking, the goodness-

Table 2 Injury severity results for Bayesian pooled ordered probit and Bayesian random parameter ordered probit models

	Pooled ordered probit			Random parameter ordered probit		
Variable	**Mean**	**SD**	**Cred. interval**	**Mean**	**SD**	**Cred. interval**
Day	0.437	0.257	(−0.086,0.924)	0.635*	0.294	(0.073,1.243)
Location	1.930*	0.231	(1.501,2.432)	1.346*	0.292	(0.772, 1.887)
Crash type	−0.437*	0.138	(−0.734,-0.176)	−0.461*	0.139	(−0.735, −0.201)
Sigma^2				0.527*	0.058	(0.044,2.279)
Goodness-of-fit						
No. of observations	210			210		
DIC	272.209			260.424		

Notes: SD = Standard deviation; *denotes significance at 95% confidence interval

Table 3 Liability results for Bayesian pooled ordered probit and Bayesian random parameter ordered probit models

	Pooled ordered probit			Random parameter ordered probit		
Variable	**Mean**	**SD**	**Cred. interval**	**Mean**	**SD**	**Cred. interval**
Location	0.550*	0.180	(0.204,0.908)	0.509*	0.213	(0.069, 0.932)
Crash reason	1.569*	0.159	(1.272, 1.886)	1.591*	0.174	(1.256, 1.933)
Sigma^2				0.088*	0.123	(0.004, 0.448)
Goodness-of-fit						
No. of observations	210			210		
DIC	273.762			272.454		

Notes: SD = Standard deviation; *denotes significance at 95% confidence interval

of-fit of the proposed models perform better, thus the following explanation would concentrate on the Bayesian random parameter ordered probit models.

In Table 2, the first significant variable day is positively related to injury severity, indicating that compared to the daytime, the injury severity level is increasing at nighttime. Although there exist some AV injuries at daytime, the severity level at nighttime is more severe, which makes sense. As predicted, the severe injury probability at night increases 63.5%. The finding is uniform with the injury severity of human-driven vehicles.

As for the AV injury severity, location plays a significant role, and compared to intersections, more injuries occur at mid-block segments. The severe injury probability happens at segments increases 134.6%, and the main reason may lie in that at mid-block segments the AVs travel at higher speeds than at intersections, thus generating more chances to lead to severe injury, which is in line with actual situations.

Another significant variable influencing the injury severity of AVs is crash type. The negative sign indicates that compared to frontal and rear-end injury, the severity level of right and left collisions is slight, and the probability is decreased about 46.1%. This implies that more severe injuries of AVs are from frontal and rear-end injury, which displays that the testing performance of AVs on the road should be paid more attention to the detectors or sensors in the front and rear-end.

One doubt about the insignificant variables is the intelligence level, no matter whichever level the AVs are. The reason is such that most of the current AVs are still testing at specific sites or locations, where the human-driven vehicles may not be so many as the actual traffic conditions, thus causing the intelligence level not to be critical.

In Table 3, liability is significantly influenced by location and crash reason. Similarly, at mid-block segments, the probability of second and third party responsibility is higher than that of AV system and AV driver, implying that besides the AV itself, more liabilities come from other parties. Moreover, the liability probability increases about 50.9% at mid-block segments than that at intersections. Therefore, besides the AV itself, the coordinated infrastructure and facilities at mid-block segments should be matched equally.

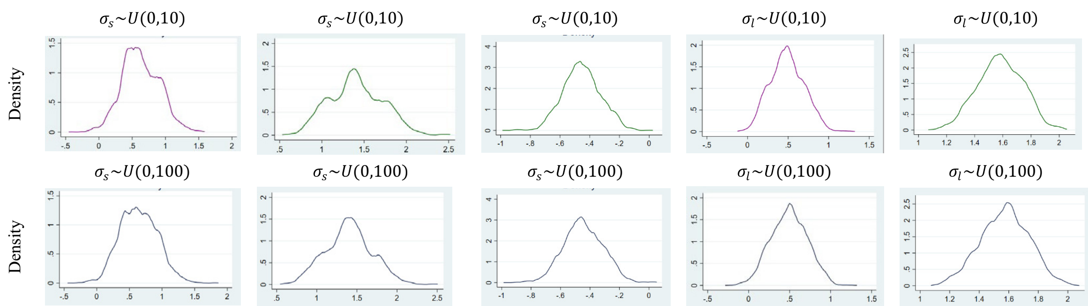
Identically, crash reason reveals a positive relation with the liability, implying that the liability probability from second party driver wrong operation and non-motorized vehicles is higher than that from AV driver wrong operation and malfunction. Furthermore, the liability probability is increased 159.1%, which verifies that besides AV itself, more responsibility comes from the human-driven vehicles and non-motorized vehicles.

To validate the results of Bayesian analysis, sensitivity analysis of prior specifications is conducted. Followed the suggestion by Xu *et al.* (2022), the results are shown in Figure 2, which indicates that the parameters are insensitive and robust to prior specifications and the data are adequate to draw robust and credible inferences.

6. Discussion

As stated above, there have been different approaches about the AV safety. However, most of the studies concentrate on qualitative discussion. In this study, to deal with quantitative analysis of AV safety and liability, the Bayesian random parameter ordered probit models are proposed, respectively, which can address the AV safety and liability correspondingly, and accommodate the heterogeneity issue due to unobserved effects.

Figure 2 Sensitivity analysis of variance (σ_s and σ_l are for safety and liability)



Shown from Tables 2 and 3, the closer examination of the comparison results provides some similarities and differences among the models. First, the similarity lies in that for all the significant variables, Bayesian pooled and random parameter ordered probit models almost display the same significant factors, and location is significant for both safety and liability. This indicates that AV safety and liability are impacted by the specific variables respectively. Second, the difference lies in that the injury severity levels of AVs are impacted by the crashes features, whereas the liability comes more from other parties besides AV itself. Third, there is no endogeneity between injury severity and liability, which means that they are not influenced by each other. This implies that safety and liability are only reflected by influencing factors.

Empirically, shown from the model results, the current testing of AVs may be conducted in the daytime as the injury level is more severe at night, meanwhile at nighttime the detecting performance of AVs should be improved to avoid severe injury. As the injury is more severe at mid-block segments than that at intersections, corresponding measures should be taken to alert the AVs from high speed traveling, e.g. automatic speed limit reduction. To reduce frontal and rear-end crashes, more advanced detectors and sensors should be installed and tested in AVs. The liability results verify that besides AV itself, the infrastructure, communication, facilities and devices should be coordinated so that V2X can be reached precisely. At last, more regulations and policies about AVs should be issued so that each party can understand individual's responsibility more clearly.

7. Conclusions

In this study, to investigate the safety and liability of AVs, and accommodate the heterogeneity issue due to unobserved effects, Bayesian random parameter ordered model was proposed to identify the significant influencing factors of injury severity and responsibility. The results revealed that day, location and crash type were significant factors of injury severity while location and crash reason were significant influencing the liability.

Two main findings can be obtained from the results. First, this is the initial attempt to use the actual AV crashes to investigate the safety and liability quantitatively, which can be considered as a critical foundation. Second, Bayesian random parameter ordered probit model can not only reflect the safety and liability of AVs, respectively, but also accommodate the heterogeneity issue simultaneously, which expands the range of the proposed model.

Some drawbacks may need to be improved in the future study. As the testing of AVs is still on the way, and more problems still come up, more related parameters should be collected so that safety and liability can be reflected more completely. Due to the data set limitation, more related factors influencing AVs should be collected in the coming work. Future study may consider safety spatially and temporally, so that spatial and temporal issues can be addressed accordingly. More issues about AVs, e.g. equity, ethics and industry risks may be available, at this time a multivariate dependent variable approach is an alternative and all may form a structural equation models, which is worthy of attempting.

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