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Bivariate joint analysis of injury severity of drivers in truck-car crashes accommodating multilayer unobserved heterogeneity

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ABSTRACT

Truck-involved crashes, especially truck-car crashes, are associated with serious and even fatal injuries, thus necessitating an in-depth analysis. Prior research focused solely on examining the injury severity of truck drivers or developed separate performance models for truck and car drivers. However, the severity of injuries to both drivers in the same truck-car crash may be interrelated, and influencing factors of injury severities sustained by the two parties may differ. To address these concerns, a random parameter bivariate probit model with heterogeneity in means (RPBPHM) is applied to examine factors affecting the injury severity of both drivers in the same truck-car crash and how these factors change over the years. Using truck-car crash data from 2017 to 2019 in the UK, the dependent variable is defined as slight injury and serious injury or fatality. Factors such as driver, vehicle, road, and environmental characteristics are statistically analyzed in this study. According to the findings, the RPBPHM model demonstrated a remarkable statistical fit, and a positive correlation was observed between the two drivers' injury severity in truck-car crashes. More importantly, the effects of the explanatory factors showing relatively temporal stability vary across different types of vehicle crashes. For example, car driver improper actions and lane changing by trucks, have a significant interactive effect on the severity of injuries sustained by drivers involved collisions between trucks and cars. Male truck drivers, young truck drivers, older truck drivers, and truck drivers' improper actions, elevate the estimated odds of only truck drivers; while older car and unsignalized crossing increase the possibility of injury severity of only car drivers. Finally, due to shared unobserved crash-specific factors, the 30-mph speed limit, dark no lights, and head-on collision, significantly affect the severity of injuries sustained by drivers involved in collisions between trucks and cars. The modeling approach provides a novel framework for jointly analyzing truck-involved crash injury severities. The findings will help policymakers take the necessary actions to reduce truck-car crashes by implementing appropriate and accurate safety countermeasures.

1. Introduction

Freight transportation systems are crucial to the economic development of countries. In the UK, about 136.4 billion tons-km of goods were moved in 2020 (Department for Transport Statistics by UK, 2017). In the US, the daily amount of goods delivered is around 55 million tons (U.S. Department of Transportation, 2017). However, given their size and weight, trucks often bring significant safety problems to roadways (Behnood and Mannering, 2019). Serious or even fatal injuries occur more likely in truck-related collisions than in other vehicle collisions (Ahmed et al., 2018). Trucks were involved in about half of all crashes on I-80 in Wyoming between 2007 and 2016 (Haq et al., 2022). And during this period, 72 % of the fatalities in crashes involving trucks were occupants in other vehicles demonstrating that if a passenger car collides with a truck, the occupants have a greater likelihood of being seriously injured or even killed (NHTSA, 2018), thus necessitating an in-depth analysis for the level of injury severity experienced by drivers in collisions between trucks and cars.

Since both drivers in the same truck-car crash share the surrounding environment (e.g., road-, weather-, and light- conditions) and each driver's behavior and vehicle type can affect the other driver's injury severity, their injury severity may be interrelated. In recent years,

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studies have paid attention to this issue in two-vehicle crashes[1]. Rana et al. (2010) developed a copula-based method to simultaneously model both drivers' injury severities involved in two-vehicle crashes, suggesting a significant relationship between the two driver injury severity outcomes. Chiou et al. (2020) also supported this association using a generalized estimating equations approach. In addition, some scholars have used the bivariate ordered probit method to simultaneously model both drivers' injury severities (Chiou et al., 2013; Li et al., 2017). Their consistent findings indicated that the model's performance would be underestimated and thus lead to biased parameter estimation as well as not practically indicative results if the relationship between the severity of injuries sustained by the two drivers involved in the two-vehicle collision is not considered. Therefore, two drivers' injury severities in the same truck-car crash extracted from two-vehicle crashes based on vehicle types need to be modeled and analyzed simultaneously rather than separately.

In addition to potential correlation, the unobserved heterogeneity makes the effect of variables may be random across individuals (Mannering et al., 2016). Accordingly, in recent years, the analysis of two driver injury severity outcomes in the same rear-end crash has been conducted by several scholars using a random parameters bivariate ordered probit model (i.e., RPBOP) (Chen et al., 2019). However, the random parameters modeling approach in the studies above assumed the random parameter distributions to be independent (Mannering et al., 2016). The probability of explanatory factors affecting the means and variances of the random parameters has not been considered. To solve this problem, a random parameter with heterogeneity in means and variances approach is leveraged, which can capture multilayered unobserved heterogeneity (Savolainen et al., 2011; Mannering and Bhat, 2014; Mannering et al., 2016). However, in crash injury severity studies, this advanced method, by accommodating variables that influence the mean and variance of the parameter density function of the random parameters, is used more for univariate analysis (Behnood and Mannering, 2019; Waseem et al., 2019; Wang et al., 2022a, b), than has been used in analyzing multivariate crash injury severity. Accordingly, a more advanced random parameter bivariate modeling approach should be considered to deeply research the internal relationship between the two driver injury severity outcomes and the heterogeneity effect of significant factors.

Temporal instability is another issue that is often considered in traffic safety analysis (see details for Mannering, 2018). In order to formulate more time-sensitive and long-term strategies to enhance traffic safety, we need to explore the temporal stability effects of significant variables from a safety perspective. Most previous univariate crash injury severity studies have demonstrated the temporal instability effects of variables (i.e., Se et al., 2021; Wang et al., 2022b; Yan et al., 2022), with some variables being statistically significant in only one time period, while other variables have significantly stable effects in all time periods. However, so far, few scholars have considered the temporal effects of significant variables in a bivariate model of injury severity for both drivers. Compared to univariate driver-injury severity studies, the temporal effects of significant variables in a bivariate model are more complex, with the impacts of the influencing factors varying across time periods for a specific vehicle type and across different vehicle types (truck or car). Therefore, it is necessary to conduct further analysis for the impacts of the time-varying factors that affect the severity of injuries sustained by both drivers in a truck-car crash and then formulate more time-efficient measures based on the significant variables that produce temporal stability.

[1] The vehicle type indicator was independent variable.

In this paper, we applied a random parameter bivariate probit model with heterogeneity in means[2] to simultaneously investigate the injury severity of both parties involving truck-car crashes, using crash data obtained from the UK over three years (2017–2019). The main contribution is applying an advanced modeling approach, including potential correlation in injury severity of drivers in truck-car crashes and multilayer unobserved heterogeneity in means and variances, to the highly concerned truck-car crashes and simultaneously modeling both drivers' injury severities. The second aim of this paper is to explore the potentially different effects of the explanatory factors that exhibit relatively temporal stability. Some explanatory variables may have an interactive effect or have a significant effect on only one party. The results about different effects could be used to help provide more targeted guidelines to reduce truck-car crash injury severities.

The remaining sections are organized: Section 2 presents a comprehensive analysis of existing research on the severity of injuries sustained in truck accidents. Section 3 describes the data used for this study, followed by Section 4, focusing on the methodological approach. Then, the temporal instability is explored by likelihood ratio tests in Section 5. Section 6 discusses the model results in detail. Finally, the conclusions and potential directions of this study are conducted.

2. Literature review

In recent years, many researches have extensively studied the severity of truck-involved crashes and have contributed many valuable findings (Table 1 summarizes relevant studies over the last decade). From Table 1, it is concluded that some scholars examined the factors influencing single-vehicle truck crash injury severities (i.e., Naik et al., 2016; Zou et al., 2017; Rahimi et al., 2020); others investigated the factors influencing multi-vehicle truck crash injury severities (i.e., Uddin and Huynh, 2017; Behnood and Mannering, 2019). Here we briefly review those studies focusing on two-vehicle crash injury severities in recent years, which are more relevant to our research. The relevant studies are broadly divided into two categories in terms of modeling approaches: univariate and bivariate statistical modeling studies.

2.1. Studies about injury severities involving truck-car crashes based on univariate statistical models

Among multi-vehicle crashes involving trucks, truck-car crashes account for the highest proportion, resulting in greater injury severity for drivers (Shao et al., 2020; Haq et al., 2022). Table 1 shows us that several scholars developed separated performance models to explore the factors that play a role in determining the injury severities of truck and car drivers in truck-car crashes. An investigation into the factors that impact the severity of injuries resulting from different types of crashes was conducted based on the heteroscedastic ordered logit models by Lee and Li (2014). Their findings of the models indicate that certain variables such as angle, sideswipe, abnormal condition, weekend, and undivided significantly impact the severity of injuries experienced by truck drivers, while other variables such as female, improper action, and vehicle age significantly affect the injury severity of car drivers exclusively. Moreover, certain explanatory variables may have a combined effect on the injury severity of drivers in two-vehicle collisions. In another study, Shao et al. (2020) employed random parameters ordered probit models to distinguish the variations in factors that impact injury severity in rear-end crashes involving car-strike-truck and truck-strike-car scenarios. Their results significantly differ in contributing factors

[2] We tried using a more generalized formulation to calculate the variance of the parameter density function for the random parameters. However, we couldn't identify any statistically significant determinants of the standard deviations.

Table 1
Summary of studies on truck-involved crash injury severities.

Authors	Study area	Methods	Truck-car crashes (Y/N)	Research highlights
Lee and Li, 2014	Ontario, Canada	Heteroscedastic ordered logit	Y	The influences of factors on crash injury severities in vehicle types (such as single-car and car-car crashes or car-car and truck-truck crashes) are different.
Weng et al., 2014	Singapore	Rear-end crash risk model	Y	Among the various vehicle following patterns, the car-truck has the greatest risk of rear-end collisions, with the truck-truck, truck-car, and car-car patterns ranking successively lower in terms of crash risk.
Chen et al., 2015	New Mexico	Hierarchical Bayesian random intercept	N	Roadways with grades, single-vehicle, and maximum vehicle damage increase driver injury severities. In addition, the interactive effects between factors tend to significantly affect truck-involved crash injury severities.
Naik et al., 2016	Nebraska, U.S.	Ordered and multinomial logit	N	Weather conditions, such as temperature, humidity, wind speed, and rain, significantly affect injury severity involving single-vehicle truck crashes.
Osman et al., 2016	Minnesota State, U.S.	Multinomial, nested, and ordered logit	N	Factors, including daytime, rural principal arterials, no access control, and higher speeds, significantly increased the injury severities involving large truck crashes in work zones.
Al-Bdairi and Hernandez, 2017	Oregon State, U.S.	Random parameters ordered probit	N	Non-license drivers were more likely to emerge from run-off-road crashes without injuries. However, if the crash was caused by human-related factors (such as fatigue), the probability of minor injuries increased.
Uddin and Huynh, 2017	Ohio State, U.S.	Mixed logit	N	Various factors, including the age and gender of the occupants, the type of truck, the AADT, the speed, and the weather conditions, significantly impacted the truck-involved crash injury severities.
Zou et al., 2017	New York, U.S.	Spatial generalized ordered probit	N	Crashes during the afternoon and at night exhibited varying degrees of severity depending on the number of vehicles involved. Single-vehicle crashes tended to be less severe, whereas multi-vehicle crashes were found to be more severe.
Newnam et al., 2018	U.S.	Chi-square statistics	N	Older truck drivers were more likely to drive safely (i.e., with safety belts) than middle-aged ones.
Zheng et al., 2018	North Dakota and Colorado, U.S.	Gradient boosting data mining	N	The characteristics of trucking companies and drivers have been shown to play a significant role in determining the severity of injuries resulting from commercial truck crashes.
Behnood and Mannering, 2019	Los Angeles, U. S.	Random parameters logit	N	The study found some influencing factors had relatively consistent effects on truck-involved crash injury severities over time, including sideswiping, hitting parked vehicles or fixed objects, and

(continued on next page)

Table 1 (*continued*)

Authors	Study area	Methods	Truck-car crashes (Y/N)	Research highlights
				accidents in which the truck driver was responsible for the collision.
Wang and Prato, 2019	China	Partial proportional odds model	N	Some factors associated with crash injury severity include driving without license, not wearing seat belts, and drunken driving.
Azimi et al., 2020	Florida, U.S.	Random parameter ordered logit	N	Compared to previous studies, unpaved shoulders, hazardous material release, and tire defects are significant unique factors influencing large truck rollover crash injury severities.
Behnood and Al-Bdairi, 2020	Florida, U.S.	Random parameters logit	N	The impacts of influencing factors (including the driver-, vehicle-, roadway-, weather-, and temporal-characteristics related) are different between weekdays and weekends.
Haq et al., 2020	Wyoming, U.S.	Bayesian binary logit model	Y	The effects of the explanatory factors, including the driver-, roadway-, weather-, and crash-related characteristics, are found to vary across vehicle-type crashes.
Rahimi et al., 2020	Iran	Random parameters ordered probit	N	Single-truck driver injury severity was found to be significantly associated with driver's education, advanced braking system deployment, roadway curves, and high-speed limits.
Song and Fan, 2020	North Carolina, U.S.	Partial proportional odds model	N	The severity of intersection accidents is mainly due to drivers disregarding signs, improperly using lanes, following too closely, ignoring signals, and failing to yield.
Uddin and Huynh, 2020	Ohio, U.S.	Mixed logit	N	The impact of influential factors on the severity of truck-related crash injuries varied depending on the prevailing weather conditions.
Shao et al., 2020	U.S.	Random parameters ordered probit	Y	The factors contributing to injury severity differed depending on whether the crash involved a car striking a truck or a truck striking a car.
Haq et al., 2021	Wyoming, U.S.	Hierarchical Bayesian random intercept approach	N	The age, gender, residency, license restrictions, involvement of multiple vehicles, run-off-road incidents, presence of work zones and junctions, and type of median were identified as having significantly different impacts on driver injury severity, depending on the specific configuration of the truck involved.
Hosseinzadeh et al., 2021	Iran	SVM and random parameter logit	N	Fatigue and deviation to the left significantly increased the fatal injuries of the large truck driver who was responsible for the crash.
Islam et al., 2022	North Carolina, U.S.	Mixed logit	N	Multiple factors, such as demographics, driver physical condition, driver actions, restraint usage, roadway and traffic, environment, vehicle, and crash characteristics, interact in a complex way.

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Table 1 (*continued*)

Authors	Study area	Methods	Truck-car crashes (Y/N)	Research highlights
Wang et al., 2022b	China	Random parameters logit	N	The results showed the influences of factors were significantly different between crashes involving trucks and those not involving trucks.
Haq et al., 2022	Wyoming, U.S.	Bayesian binary logit model	Y	Collisions between cars and trucks often result in more serious injuries, and it is commonly observed that car drivers tend to be more responsible than truck drivers in such situations.

towards injury severity, including age group, trailing units, drinking driving, and road surface. However, their study was constrained to truck-involved rear-end crashes. Haq et al. (2020) utilized a Bayesian inference approach with a binary logistic model to examine the factors that affect the injury severity of both truck and car drivers involved in truck-car crashes, separately. Their results show that driver-related characteristics (such as age, gender, occupation, and residency), the roadway (curves, downgrades, and presence of junctions), and weather conditions significantly impact injury severities in different vehicle types involving truck crashes. Certain inappropriate driving behaviors exhibited by car drivers substantially raise the injury severity of truck drivers.

The studies above developed separate models for truck and car driver-injury severities and concluded many valuable findings. However, traditional separated performance models can not reveal a correlation between the severity of injuries sustained by both parties in the same collision. The underlying correlation of injury results between occupants engaged may result from common unobserved factors (Russo et al., 2014). Ignoring these potentially shared unobserved crash-specific factors could cause inefficiencies in model parameter estimation (Abay et al., 2013; Chiou et al., 2013).

2.2. Studies about injury severities involving two-vehicle crashes based on bivariate statistical models

To overcome the shortcomings of univariate model studies, some scholars develop bivariate probit models to explore the factors that impact the severity of injuries for both parties involved in an incident at the same time (Chiou et al., 2013; Li et al., 2017). However, the conventional bivariate models treat the significant parameters as fixed, which may result in biased and inconsistent model estimation and even conclusions with no practical guidance (Mannering et al., 2016). Accordingly, in recent years, several researchers have estimated random parameters bivariate ordered probit models for modeling the injury severity of both drivers in the same crash. Specifically, Abay et al. (2013) used the RPBOP models to simultaneously analyze the injury severity of both drivers in the same two-vehicle crash. Their findings revealed correlations and unobserved heterogeneity. To investigate the correlation and unobserved heterogeneity in injury outcomes among at-fault and not-at-fault drivers involved in angle crashes, Russo et al. (2014) also used the RPBOP models. They found a positive correlation in injury outcomes between both drivers. Chen et al. (2019) also used the RPBOP models to investigate variables that contribute to the two driver injury severity outcomes in the same rear-end crash between two passenger cars. Wang et al. (2021) used random parameters bivariate probit models to examine the severity of injuries sustained by motorcycle riders and pillion passengers. As mentioned earlier, the research has corroborated a meaningful correlation between two driver injury severity outcomes in two-vehicle collisions and the heterogeneous impact of influencing factors on the injury severity of both drivers.

However, the random parameters bivariate modeling approach in the studies above assumed that the distribution of random parameters was independent (Mannering et al., 2016). The possibility of explanatory factors affecting the individual parameter estimates has not been accounted for. To address this issue, a random parameters bivariate modeling approach with heterogeneity in means and variances is developed, which is capable of capturing multilayered unobserved heterogeneity (Islam and Mannering, 2020). However, this new approach has only been used to conduct an analysis of autonomous vehicles (Ahmed et al., 2020) or driving behavior (Sarwar et al., 2017; Fountas et al., 2019). The application of this approach in the analysis of two-vehicle crash injury severity, especially for truck-car crashes, appears to be rather limited.

Therefore, a more advanced random parameter bivariate modeling approach should be considered to deeply research the heterogeneity of crash data that occurred in truck-car crashes. To that end, using truck-car crash injury-severity data that happened in the UK from 2017 to 2019, this paper examines whether the driver injury severities and the effects of influencing factors vary across different types of vehicle crashes and different time periods using the random parameters bivariate probit model with heterogeneity in means (RPBPHM).

3. Data description

The truck-car crashes in the UK between 2017 and 2019 were drawn from the STATS19 dataset, which is one of the most publicly available crash databases in the UK (Department for Transport, 2019). The dataset comprises three files: accident, vehicle, and casualty. We used the accident and vehicle reference numbers provided for this study to merge the three sub-sets. Each case contains driver-related characteristics (age and gender of the driver and injury-severity level), vehicle-related characteristics (vehicle type and vehicles' maneuvers), roadway characteristics (road type, posted speed limit), and crash-related characteristics (time/date of accident occurrence, weather conditions, light conditions, and type of collision). In this study, a truck-car crash is defined as two-vehicle collisions with a passenger vehicle and a truck (light, medium, or heavy truck) involved. A light truck is considered to weigh less than 7,840 lb, a medium truck between 7,840 lb and 16,800 lb, and a heavy truck is more than 16,800 lb (Department for Transport, 2019). The data of 18,626 truck-car crashes were extracted.

Following the STATS19 injury classification, the injury severities are classified into slight, serious, and fatal injury. It should be noted that this original dataset only includes collisions that resulted in injuries, and collisions without any injuries are not documented (Fountas and Rye, 2019). This is categorized as fatal, serious, or slight and accounts for 0.64%, 10.34%, and 89.02% for truck drivers and 1.51%, 12.26%, and 86.23% for car drivers, respectively. Table 2 presents the frequency distribution for various crash severity categories. Because the proportion of fatalities is too small, this study reclassifies cases using two severity levels: slight injury and serious injury or fatality (including serious injury and fatal injury). The descriptive statistics for the variables used in injury severity models are presented in Table 3.

4. Methodology

To account for the multilayered unobserved heterogeneity of truck-

Table 2
Frequency distribution of the crash injury severity categories.

Year	Fatal injury Truck driver	Car driver	Serious injury Truck driver	Car driver	Slight injury Truck driver	Car driver	Total
2017	48 (0.64%)	106 (1.42%)	671 (9.00%)	842 (11.29%)	6736 (90.36%)	6507 (87.28%)	7455 (100%)
2018	29 (0.55%)	75 (1.41%)	570 (10.71%)	666 (12.52%)	4722 (88.74%)	4580 (86.07%)	5321 (100%)
2019	43 (0.74%)	100 (1.71%)	684 (11.69%)	775 (13.25%)	5123 (87.57%)	4975 (85.04%)	5850 (100%)

car crash data in terms of **(a)** factors varying across the observations; **(b)** factors affecting the mean of the parameter density function of the random parameters (and thus shifts in the peak of the distribution of the betas). This paper applies random parameters bivariate probit models with heterogeneity in means to identify factors influencing drivers' injury severity of truck-car crashes. The way in which the bivariate probit model is defined is as follows (Washington et al., 2020),

$$Y_{i,1} = \beta_{i,1}X_{i,1} + \varepsilon_{i,1}, y_{i,1} = 1 if Y_{i,1} > 0, 0 otherwise$$

$$Y_{i,2} = \beta_{i,2}X_{i,2} + \varepsilon_{i,2}, y_{i,2} = 1 if Y_{i,1} > 0, 0 otherwise \tag{1}$$

where the error terms are defined as,

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

The relationship between explanatory variables and drivers' injury severity in truck-car crashes is captured by a vector $\boldsymbol{X}$. The corresponding estimable parameters are represented by vector $\boldsymbol{\beta}$. The aggregated dependent variables, which are characterized by binary outcomes, are $\boldsymbol{y}_{i,1}$ and $\boldsymbol{y}_{i,2}$. The corresponding latent variables are $\boldsymbol{Y}_{i,1}$ and $\boldsymbol{Y}_{i,2}$. The normal joint distribution of the errors $\boldsymbol{\varepsilon}_{i,1}$ and $\boldsymbol{\varepsilon}_{i,2}$ has a zero mean and a variance of one. The correlation coefficient $\boldsymbol{\rho}$ represents the cross-equation error correlation. The cumulative bivariate normal probability distribution function and its associated log-likelihood functions can be found in Greene's (2017) work.

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

And,

$$\sum_{i=1}^{N}\left[y_{i,1}y_{i,2}ln\Phi(\boldsymbol{\beta}_{i,1}\boldsymbol{X}_{i,1}, \boldsymbol{\beta}_{i,2}\boldsymbol{X}_{i,2}, \rho) + (1-y_{i,1})y_{i,2}ln\Phi(-\boldsymbol{\beta}_{i,1}\boldsymbol{X}_{i,1}, \boldsymbol{\beta}_{i,2}\boldsymbol{X}_{i,2}, -\rho) + (1-y_{i,2})y_{i,1}ln\Phi(\boldsymbol{\beta}_{i,1}\boldsymbol{X}_{i,1}, -\boldsymbol{\beta}_{i,2}\boldsymbol{X}_{i,2}, -\rho) + (1-y_{i,1})(1-y_{i,2})ln\Phi(-\boldsymbol{\beta}_{i,1}\boldsymbol{X}_{i,1}, -\boldsymbol{\beta}_{i,2}\boldsymbol{X}_{i,2}, \rho)\right] \tag{4}$$

where the cumulative probability distribution function is denoted by $\Phi(.)$, and the remaining terms have been defined previously.

Further, in Eq. (1), the multilayer unobserved heterogeneity is taken into consideration by incorporating β_n, which is defined as (Mannering et al., 2016),

$$\beta_i = \boldsymbol{b} + \lambda\boldsymbol{Y}_i + \delta_i \tag{5}$$

In this context, the $\boldsymbol{b}$ represents the mean parameter estimate for all crashes. The explanatory variables Y_i, which are associated with crash i, influence the mean of the parameter β_i. The vector λ comprises estimable parameters, while δ_i is a disturbance term with zero mean and variance equal to σ^2.

To estimate the parameters β_i of the random parameters bivariate probit models, in a computationally efficient manner, this study employs a simulated maximum likelihood approach with 1200 Halton draws. The model estimation is based on the work of McFadden and Train (2000). Previous research has found that the normal distribution can provide the most appropriate statistical fit when examining the distribution of random parameters (Anastasopoulos and Mannering, 2011; Behnood and Mannering, 2017; Fountas et al., 2018). Pseudo-elasticities for binary indicator variables are computed as follows (Ahmed et al., 2020; Washington et al., 2020),

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

5. Temporal transferability

To evaluate the temporal transferability of the estimated parameters across different time periods that involve truck-car collisions, we used the following alteration of the likelihood ratio test (Mannering, 2018; Washington et al., 2020; Hou et al., 2022; Pang et al., 2022):

$$\chi_1^2 = -2\left[LL(\beta_{t_2t_1}) - LL(\beta_{t_1})\right] \tag{7}$$

where $LL(\beta_{t_2t_1})$ represents the log-likelihood obtained at the convergence of a model that uses data from time-period t_1, where the parameters have been estimated based on the data from time-period t_2. In contrast, $LL(\beta_{t_1})$ represents the log-likelihood obtained at the convergence of a model that uses data from time-period t_1 only, and the parameters have been estimated based on that data.

Table 4 presents the likelihood ratio test results conducted across various time periods to determine if the null hypothesis of stability over two years can be rejected. In the majority of cases, two-year periods are found to be unequal, with the null hypothesis being rejected with a confidence level exceeding 99%. The result suggests that the estimated parameters exhibit temporal transferability, and separate models are warranted by the study period.

Another series of likelihood ratio tests are simulated to estimate the temporal stability between the combined model and each separate model (Hou et al.,2022; Wang et al., 2022c; Song et al., 2023):

$$\chi_2^2 = -2\left[\mathrm{LL}(\beta_{2017-2019}) - \sum_{2017}^{2019}\mathrm{LL}(\beta_t)\right] \tag{8}$$

where $\mathrm{LL}(\beta_{2017-2019})$ denotes the log-likelihood at the convergence of the model in the three years (2017–2019), while $\mathrm{LL}(\beta_t)$ expresses the log-likelihood at the convergence of the models using one specific year t data (2017/2018/2019). The model estimate gained from the test gave an χ^2 values of 150.42 with 41 degrees of freedom. The modeling approach specified the null hypothesis that statistically significant parameters in truck-car crash models are stable can be rejected at 99.99% confidence level.

Other than using pairwise likelihood ratio tests to assess the performance of one model estimated using the data in one time period fitting the data in the following time period (Washington et al., 2020), out-of-sample prediction has been confirmed as another adequate method to analyze temporal instability in the recent studies (Hou et al., 2022; Wang et al., 2022c). Out-of-sample prediction calculates the difference in prediction probability to explicitly test the non-transferability of the parameters estimated through different disaggregated subgroup datasets.

As for temporal instability, Table 5 lists the differences (mean values) in prediction probability based on different datasets (adopting the specific year's truck-car crash model parameters to predict the injury severity outcomes based on data in the following year period). The results show that the 2017 truck-car crash model overestimated serious injury or fatality (SFI) by 0.0017, 0.0011, respectively, in 2018 and 2019 truck-car crash, while the 2018 truck-car crash model underestimated

Table 3
Descriptive statistics of variables.

Variables	All Mean	All SD	2017 Mean	2017 SD	2018 Mean	2018 SD	2019 Mean	2019 SD
Driver characteristics								
Male truck driver (1 if male truck driver, 0 otherwise)	0.588	0.492	0.589	0.492	0.592	0.491	0.583	0.493
Female truck driver (1 if female truck driver, 0 otherwise)	0.412	0.492	0.411	0.492	0.408	0.491	0.417	0.493
Male car driver (1 if male car driver, 0 otherwise)	0.575	0.494	0.576	0.494	0.574	0.495	0.576	0.494
Female car driver (1 if female car driver, 0 otherwise)	0.425	0.494	0.424	0.494	0.426	0.495	0.424	0.494
Teen-age truck driver (1 if truck driver age below 25 years, 0 otherwise)	0.240	0.427	0.245	0.430	0.244	0.430	0.229	0.420
Young truck driver (1 if truck driver age between 26 and 45 years, 0 otherwise)	0.392	0.488	0.403	0.490	0.386	0.487	0.385	0.487
Middle-aged truck driver (1 if truck driver age between 46 and 65 years, 0 otherwise)	0.233	0.423	0.228	0.420	0.238	0.426	0.237	0.425
Older truck driver (1 if truck driver age above 65 years, 0 otherwise)	0.130	0.336	0.119	0.324	0.128	0.335	0.144	0.352
Teen-age car driver (1 if car driver age below 25 years, 0 otherwise)	0.158	0.365	0.165	0.371	0.158	0.365	0.149	0.356
Young car driver (1 if car driver age between 26 and 45 years, 0 otherwise)	0.420	0.494	0.425	0.494	0.421	0.494	0.414	0.493
Middle-aged car driver (1 if car driver age between 46 and 65 years, 0 otherwise)	0.318	0.466	0.313	0.464	0.321	0.467	0.324	0.468
Older car driver (1 if car driver age above 65 years, 0 otherwise)	0.098	0.297	0.090	0.287	0.098	0.297	0.107	0.310
Truck driver home area type (1 if urban area, 0 otherwise)	0.647	0.478	0.670	0.470	0.605	0.489	0.656	0.475
Truck driver home area type (1 if small town, 0 otherwise)	0.106	0.308	0.104	0.305	0.096	0.295	0.117	0.322
Truck driver home area type (1 if rural, 0 otherwise)	0.148	0.356	0.145	0.352	0.134	0.341	0.166	0.372
Car driver home area type (1 if urban area, 0 otherwise)	0.631	0.483	0.657	0.475	0.580	0.494	0.643	0.479
Car driver home area type (1 if small town, 0 otherwise)	0.110	0.312	0.106	0.308	0.098	0.298	0.124	0.330
Car driver home area type (1 if rural, 0 otherwise)	0.162	0.369	0.159	0.366	0.155	0.362	0.174	0.379
Driving dangerous from car drivers (1 if yes, 0 otherwise)	0.030	0.170	0.029	0.168	0.032	0.175	0.029	0.167
Driving dangerous from truck drivers (1 if yes, 0 otherwise)	0.005	0.074	0.005	0.071	0.006	0.076	0.006	0.075
Vehicle characteristics								
New truck vehicle (1 if the truck is below 3 years, 0 otherwise)	0.172	0.377	0.170	0.375	0.176	0.381	0.171	0.377
Middle-aged truck vehicle (1 if the truck is 3–10 years, 0 otherwise)	0.412	0.492	0.421	0.494	0.412	0.492	0.400	0.490
Older truck vehicle (1 if the truck is above 10 years, 0 otherwise)	0.330	0.470	0.325	0.469	0.327	0.469	0.337	0.473
New car vehicle (1 if the car is below 3 years, 0 otherwise)	0.187	0.390	0.190	0.392	0.183	0.387	0.187	0.390
Middle-aged car vehicle (1 if the car is 3–10 years, 0 otherwise)	0.439	0.496	0.438	0.496	0.444	0.497	0.436	0.496
Older car vehicle (1 if the car is above 10 years, 0 otherwise)	0.278	0.448	0.279	0.449	0.272	0.445	0.283	0.450
Truck manoeuvre (1 if trucks waiting to go prior to an accident, 0 otherwise)	0.016	0.125	0.014	0.119	0.017	0.131	0.017	0.128
Truck manoeuvre (1 if trucks slowing or stopping prior to an accident, 0 otherwise)	0.042	0.200	0.047	0.212	0.042	0.201	0.034	0.181
Truck manoeuvre (1 if trucks moving off prior to an accident, 0 otherwise)	0.052	0.221	0.055	0.229	0.050	0.217	0.049	0.216
Truck manoeuvre (1 if trucks turning right prior to an accident, 0 otherwise)	0.244	0.430	0.244	0.430	0.250	0.433	0.240	0.427
Truck manoeuvre (1 if trucks changing lane to the left prior to an accident, 0 otherwise)	0.018	0.133	0.018	0.133	0.020	0.138	0.017	0.128
Truck manoeuvre (1 if trucks going ahead without taking a right-hand bend or a left-hand bend, 0 otherwise)	0.585	0.493	0.579	0.494	0.578	0.494	0.601	0.490
Car manoeuvre (1 if cars waiting to go prior to an accident, 0 otherwise)	0.015	0.120	0.016	0.126	0.013	0.115	0.014	0.117
Car manoeuvre (1 if cars slowing or stopping prior to an accident, 0 otherwise)	0.040	0.197	0.042	0.200	0.042	0.201	0.036	0.187
Car manoeuvre (1 if cars moving off prior to an accident, 0 otherwise)	0.060	0.238	0.066	0.248	0.056	0.229	0.057	0.231
Car manoeuvre (1 if cars turning right prior to an accident, 0 otherwise)	0.022	0.146	0.023	0.151	0.024	0.153	0.018	0.133
Car manoeuvre (1 if cars changing lane to the left prior to an accident, 0 otherwise)	0.109	0.312	0.111	0.314	0.114	0.317	0.103	0.305
Car manoeuvre (1 if cars going ahead without taking a right-hand bend or a left-hand bend, 0 otherwise)	0.727	0.446	0.714	0.452	0.724	0.447	0.745	0.436
Head-on collision (1 if head-on collision, 0 otherwise)	0.682	0.466	0.671	0.470	0.695	0.464	0.698	0.462
Rear-end collision (1 if rear-end collision, 0 otherwise)	0.054	0.226	0.056	0.230	0.053	0.223	0.052	0.223
Sideswipe collision (1 if sideswipe collision, 0 otherwise)	0.256	0.436	0.266	0.442	0.251	0.433	0.248	0.432
Roadway characteristics								
Roundabout (1 if the accident occurred on a roundabout, 0 otherwise)	0.041	0.199	0.042	0.201	0.041	0.198	0.040	0.196
One-way street (1 if the accident occurred on a one-way street, 0 otherwise)	0.007	0.081	0.007	0.082	0.006	0.079	0.007	0.081
Dual carriageway (1 if the accident occurred on a dual carriageway, 0 otherwise)	0.163	0.370	0.156	0.363	0.178	0.383	0.160	0.367
Single carriageway (1 if the accident occurred on a single carriageway, 0 otherwise)	0.772	0.420	0.778	0.416	0.759	0.428	0.775	0.418
The 20-mph speed limit (1 if speed limit is 20 mph, 0 otherwise)	0.016	0.124	0.013	0.114	0.021	0.144	0.014	0.117
The 30-mph speed limit (1 if speed limit is 30 mph, 0 otherwise)	0.431	0.495	0.450	0.497	0.423	0.494	0.414	0.493
The 40-mph speed limit (1 if speed limit is 40 mph, 0 otherwise)	0.127	0.333	0.123	0.329	0.131	0.337	0.128	0.334
The 50-mph speed limit (1 if speed limit is 50 mph, 0 otherwise)	0.069	0.253	0.066	0.248	0.074	0.262	0.069	0.253
The 60-mph speed limit (1 if speed limit is 60 mph, 0 otherwise)	0.274	0.446	0.269	0.444	0.263	0.440	0.290	0.454
The 70-mph speed limit (1 if speed limit is 70 mph, 0 otherwise)	0.083	0.277	0.079	0.269	0.088	0.284	0.085	0.279
Auto traffic signal (1 if junction control is auto traffic signal, 0 otherwise)	0.105	0.307	0.110	0.312	0.104	0.306	0.101	0.302
Stop sign (1 if junction control is a stop sign, 0 otherwise)	0.009	0.092	0.008	0.086	0.010	0.101	0.008	0.091
Give or uncontrolled (1 if junction control is given way or uncontrolled, 0 otherwise)	0.478	0.500	0.488	0.500	0.478	0.500	0.465	0.499
Dry road surface (1 if dry, 0 otherwise)	0.671	0.470	0.667	0.471	0.654	0.476	0.691	0.462
Wet road surface (1 if wet, 0 otherwise)	0.306	0.461	0.312	0.463	0.321	0.467	0.285	0.452
Ice road surface (1 if f ice, 0 otherwise)	0.017	0.128	0.016	0.126	0.021	0.144	0.013	0.113
Urban area (1 if the crash occurred in an urban, 0 otherwise)	0.438	0.496	0.448	0.497	0.451	0.498	0.412	0.492
Rural area (1 if the crash occurred in a rural, 0 otherwise)	0.562	0.496	0.552	0.497	0.549	0.498	0.588	0.492
Environmental characteristics								
Daylight conditions (1 if daylight, 0 otherwise)	0.735	0.441	0.736	0.441	0.719	0.450	0.749	0.434
Darkness with lights lit (1 if darkness with lights lit, 0 otherwise)	0.163	0.370	0.168	0.374	0.170	0.375	0.151	0.359
Darkness with lights unlit (1 if darkness with lights unlit, 0 otherwise)	0.087	0.282	0.084	0.277	0.090	0.287	0.089	0.284
Fine weather conditions (1 if fine, 0 otherwise)	0.818	0.386	0.816	0.388	0.816	0.388	0.823	0.382
Inclement weather conditions (1 if rain/snow/fog, 0 otherwise)	0.140	0.347	0.143	0.350	0.145	0.352	0.131	0.337
Spring (1 if spring, 0 otherwise)	0.249	0.433	0.243	0.429	0.258	0.438	0.279	0.433
Summer (1 if summer, 0 otherwise)	0.236	0.425	0.240	0.427	0.237	0.425	0.231	0.421
Autumn (1 if autumn, 0 otherwise)	0.252	0.434	0.256	0.436	0.249	0.432	0.249	0.433
Winter (1 if winter, 0 otherwise)	0.262	0.440	0.261	0.439	0.256	0.437	0.270	0.444

(*continued on next page*)

Table 3 (*continued*)

Variables	All		2017		2018		2019	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Weekdays (1 if weekdays, 0 otherwise)	0.707	0.455	0.704	0.456	0.707	0.455	0.711	0.453
Weekends (1 if weekends, 0 otherwise)	0.293	0.455	0.296	0.456	0.293	0.455	0.289	0.453
Off-peak time (1 if crash time is off-peak time, 0 otherwise)	0.605	0.489	0.602	0.489	0.602	0.490	0.611	0.488
Morning peak time (1 if morning peak, 0 otherwise)	0.181	0.385	0.181	0.385	0.185	0.388	0.178	0.383
Evening peak time (1 if evening peak, 0 otherwise)	0.214	0.410	0.217	0.412	0.213	0.410	0.211	0.408

Table 4
Assessment of the likelihood ratio test outcomes across multiple time periods (degrees of freedom in parentheses and confidence level in brackets).

t_1 / t_2	2017	2018	2019
2017	–	222.25 (33) [99.99%]	68.82 (41) [99.59%]
2018	76.45(32) [99.99%]	–	74.07 (41) [99.88%]
2019	43.68(32) [99.92%]	194.54 (33) [99.99%]	–

Table 5
Difference in probabilities by temporal instability for truck-car crashes [slight injury - SI, serious injury or fatality - SFI].

Predict year	2017		2018		2019	
Base year	SFI	SI	SFI	SI	SFI	SI
2017	—	—	0.0017	−0.0017	0.0011	−0.0011
2018	—	—	—	—	−0.0032	0.0032

serious injury or fatality (SFI) by 0.0032 in 2019 truck-car crash. Given this, the significant differences shown in the table reveal potential temporal instability in terms of out-of-sample prediction.

6. Results and discussion

First, we also estimated univariate probit models with fixed and random parameters and compared them with their bivariate counterparts. That is, the bivariate probit model was validated by the significant testing of three cross-equation correlation coefficients (**ρ**) of the error terms for the two latent variables at a confidence level of 99.99%. The positive correlation indicates that unobserved factors jointly affect the injury severity of both drivers in the same truck-car crash. This suggests that drivers involved in the same accident may share crash-specific unobserved contributors that influence the severity of injuries in a similar way for both drivers.

Then, three modeling approaches, including the fixed parameters bivariate probit approach (BP), the random parameters bivariate probit approach (RPBP), and the random parameters bivariate probit with heterogeneity in means approach (RPBPHM), were leveraged in the statistical analysis. Table 6 displays the goodness-of-fit measures for the estimated models, which were evaluated based on the Akaike Information Criterion (AIC) and log-likelihood values at convergence. A smaller AIC value and a higher log-likelihood value at convergence indicate a better model fit, as Washington et al. (2020) reported. The results of the goodness-of-fit measures suggest that the RPBPHM approach outperforms the RPBP and BP approaches in all analysis scenarios in a statistically significant manner.

BP: Bivariate probit model; RPBP: Random parameters bivariate probit model; RPBPHM: Random parameters bivariate probit model with heterogeneity in the means.

Further, some scholars have concluded that small sample size in crash severity models can lead to erratic results, which limit their ability to estimate the true parameters and result in an inaccurate prediction of the probabilities for each severity outcome (Ye and Lord, 2014; Shirazi et al., 2016; Mao et al., 2019). To examine the potential bias associated with different sample sizes used in this study for bivariate modeling approach, we set the models estimated from the full dataset as the baseline conditions (as estimated for the year 2017/2018/2019). Then, a stratified sampling method was used for different sampling sizes: 100, 500, 1000, 2000, 4000, 5000. The stratified sampling method was used in order to keep the same proportion rates as those used for the full dataset. This is categorized as slight injury and serious injury or fatality and accounts for 90.36% (88.74%/87.57%) and 9.64% (11.26%/ 12.43%) for truck drivers and 87.28% (86.07%/85.04%), and 12.72% (13.93%/14.96%) for car drivers in the year 2017 (2018/2019), respectively. For the sake of simplicity, 10 random samples were selected for each sample size.

We then compared the results with those calculated from the baseline conditions to get the value of bias, absolute-percentage-bias (APB) and root-mean-square-error (RMSE) for each parameter. Furthermore, the mean of APB, maximum of APB and total RMSE were estimated as a function of the sample size for each model.

Based on the 10 estimated models of each sample size, for each parameter, the bias was calculated as $\text{Bias}=E(\widehat{\beta}_r)-\beta_{\text{baseline}}$, where r is the number of replications, $r = 10$, β represents each parameter in the model, and $E(\widehat{\beta}_r)$ is approximated by $\overline{\beta} = \frac{1}{r}*(\sum_{i=1}^{r}\widehat{\beta}_i)$. The APB was computed by dividing the absolute value of bias to the baseline value. The RMSE was calculated as,

$$\text{RMSE} = \sqrt{\frac{1}{N}*\sum_{k=1}^{N}\left(\frac{1}{r}*\sum_{i=1}^{r}\beta_{k,i}-\beta_{k,\text{baseline}}\right)^2} \tag{9}$$

where k refers to the number of estimated parameters. Thus, the mean of the APB among all the parameters in a model could be calculated by taking the average of the APB values of all parameters. Furthermore, the maximum of APB was found by comparing the APB value of each parameter in a model. Finally, total RMSE could easily be attained by summing up the RMSE value of each parameter in a model. The results of the comparison analysis based on the three valuation criteria described in the previous paragraph are summarized in Table 7.

From Table 7, we can conclude that, the increase in sample size leads to the reduction in all three criteria (mean of APB, max of APB and total RMSE), improving the accuracy of model. According to the three criteria, the estimated values become very close to the “true” values (baselines) when the sample size is up to 5,000. Thus, the truck-car crash datasets used in this study meet the bivariate modeling analysis.

For the sake of clarity and simplicity, we will focus solely on the results of the superior RPBPHM model in the remainder of this section. Specifically, Table 8 presents the RPBPHM model results pertaining to the injury severity of drivers involved in the same truck-car crash. Table 9 provides their magnitudes (derived from their pseudo-elasticities) on injury severities with respect to vehicles types, injury severity levels, and years. Based on the RPBPHM model results, section 6.1 gives insights from random parameters in detail; section 6.2 reveals the differences between the factors influencing the injury severities of both drivers in truck-car crashes from the driver-, vehicle-, road-, and environmental- characteristics, respectively, and formulated more refined road safety measures.

6.1. Insights from random parameters

For all-years pooled model, there are **six** statistically significant

Table 6
Goodness-of-fit measures for the estimated BP, RPBP, and RPBPHM models.

Goodness-of-fit	All years			2017			2018			2019		
measures	BP	RPBP	RPBPHM	BP	RPBP	RPBPHM	BP	RPBP	RPBPHM	BP	RPBP	RPBPHM
Number of observations	18,626	18,626	18,626	7455	7455	7455	5321	5321	5321	5850	5850	5850
Log-likelihood at zero	−16181.00	−16181.00	−16181.00	−5988.50	−5988.50	−5988.50	−5050.55	−5050.55	−5050.55	−6161.50	−6161.50	−6161.50
Log-likelihood at convergence	−12216.68	−12111.9	−12000.8	−4389.57	−4377.59	−4341.66	−3474.78	−3464.68	−3444.48	−4214.47	−4202.14	−4171.34
R-Squared	0.245	0.251	0.258	0.267	0.269	0.275	0.312	0.314	0.318	0.316	0.318	0.323
Adjusted R-Squared	0.244	0.250	0.256	0.263	0.264	0.269	0.305	0.307	0.310	0.311	0.313	0.317
Akaike information criterion (AIC)	24501.4	24303.8	24109.6	8865.14	8857.19	8801.33	7051.56	7039.35	7010.95	8514.93	8496.29	8452.67
AICc (for the number of parameters)	24501.5	24304.0	24110.0	8865.65	8857.90	8802.28	7052.56	7040.52	7012.39	8515.58	8497.03	8453.73
χ^2 test	BP vs RPBPHM	RPBP vs RPBPHM		BP vs RPBPHM	RPBP vs RPBPHM		BP vs RPBPHM	RPBP vs RPBPHM		BP vs RPBPHM	RPBP vs RPBPHM	
	431.76 (20) [> 99.99%]	222.20 (14) [> 99.99%]		95.82 (16) [> 99.99%]	71.86 (8) [> 99.99%]		60.60 (10) [>99.99%]	40.40 (6) [>99.99%]		86.26 (12) [>99.99%]	61.62 (9) [>99.99%]	

variables as random parameters (see Table 8), including young truck drivers (between 26 and 45 years), the middle-aged car driver (between 46 and 65 years), new car vehicles (3 years below), middle-aged car vehicles (between 3 and 10 years), rural areas, and the 30-mph speed limit. Among them, **(1)** the young truck driver (between 26 and 45 years) indicator is significant as a normally distributed random parameter; in 84.13% of the cases, the observations reveal a rise in the likelihood of severe injury (and in a reduction in the rest 15.87%). Note that the mean of the young truck driver indicator is affected by the darkness with lights lit indicator and winter indicators. Specifically, the young truck driver indicator, which is a random parameter, generates, 84.13% positive betas (right of the mean) and 15.87% negative betas (left of the mean), while the darkness with lights lit indicator, which results in heterogeneity in the means variable, has a negative sign, then the mean of the distribution will be shifted to the left, which will increase the number of negative betas and reduce the positive betas. This means that this shift in the mean will decreases the mean of the young truck driver indicator, thus decreasing the likelihood of severe injuries. In contrast, the winter indicator has a positive sign, then the mean of the distribution will be shifted to the right, which will increase the number of positive betas and reduce the negative betas. This means that this shift in the mean will increases the mean of the mean of indicator, making severe injuries more likely. **(2)** The middle-aged car driver (between 46 and 65 years) indicator is significant as a normally distributed random parameter, where 84.83% of the observations decrease the probability of severe injury. Note that the mean of the middle-aged car driver indicator is affected by the male indicator. Specifically, the middle-aged car driver indicator, which is a random parameter, generates, 84.83% negative betas (left of the mean) and 15.17% positive betas (right of the mean), while the male indicator, which results in heterogeneity in the means variable, has a negative sign, then the mean of the distribution will be shifted to the left, which will increase the number of negative betas and reduce the positive betas. This means that this shift in the mean will decreases the mean of the mean of the middle-aged car driver indicator, making severe injuries less likely. **(3)** The new car vehicle (3 years below) indicator and **(4)** the middle-aged car vehicle (between 3 and 10 years) indicator are significant as random parameters, with the majority of the observations having a low chance of experiencing severe injury (77.47% and 76.61%, respectively). A large potential safety hazard exists when driving older cars over ten years. Therefore, middle-aged cars (between 3 and 10 years) are recommended to be regularly maintained. **(5)** Among all truck-car crashes on rural roadways, 95.92% are severe injury crashes, while the winter indicator, which results in heterogeneity in the means variable, has a negative sign, then the mean of the distribution will be shifted to the left, which will increase the number of negative betas and reduce the positive betas. This means that this shift in the mean will decreases the mean of the young truck driver indicator, thus decreasing the likelihood of severe injuries. **(6)** The 30-mph speed limit indicator is a random parameter that holds great significance, given that the majority of observations have a low probability of experiencing severe injury (76.39% for truck drivers). The result is easy to understand intuitively, and higher speed limits have been found in the literature to be related to severe injury crashes (i.e., Osman et al., 2016). The lower speed limit should be set for sections with high crash rates if the speed limit is over 30 mph. Note that the winter indicator has a positive sign, then the mean of the distribution will be shifted to the right, which will increase the number of positive betas and reduce the negative betas. This means that this shift in the mean will increases the mean of the mean of indicator, making severe injuries more likely.

For the 2017 model, there are **six** statistically significant variables as random parameters (see Table 8), including young truck drivers (between 26 and 45 years), new car vehicles (3 years below), middle-aged car vehicles (between 3 and 10 years), rural areas, the 30-mph speed limit, and sideswipe collisions. Among them, **(1)** the young truck driver (between 26 and 45 years) indicator is significant as a normally distributed random parameter; in 79.70% of the cases, the observations

Table 7
Three evaluation criteria by sample size for the bivariate models.

Sample size	Mean of APB*			Max of APB			Total RMSE		
	2017	2018	2019	2017	2018	2019	2017	2018	2019
100	1.326	1.305	1.970	3.448	3.654	7.486	1.500	1.661	3.900
500	0.259	0.225	0.396	0.777	0.675	1.584	0.366	0.318	0.840
1000	0.163	0.106	0.148	0.408	0.318	0.814	0.173	0.150	0.471
2000	0.095	0.038	0.034	0.214	0.175	0.306	0.084	0.097	0.192
4000	0.029	0.025	0.022	0.104	0.085	0.154	0.053	0.042	0.093
5000	0.018	0.008	0.012	0.064	0.037	0.058	0.033	0.021	0.033

* APB: absolute-percentage-bias; RMSE: root-mean-square-error.

reveal a rise in the likelihood of severe injury (and in a reduction in the rest 20.30%). **(2)** The new car vehicle (3 years below) indicator and **(3)** the middle-aged car vehicle (between 3 and 10 years) indicator are significant as random parameters, with the majority of the observations having a low chance of experiencing severe injury (69.27% and 70.27%, respectively). **(4)** Among all truck-car crashes on rural roadways, 96.03% are severe injury crashes. Therefore, drivers should be alert and slow down in advance before entering rural roads, especially heterogeneous sections, whose geometrical characteristics (i.e., number of lanes, roadway width, etc.) change throughout the length of the segment. **(5)** The 30-mph speed limit indicator is a random parameter that holds great significance, given that the majority of observations have a low probability of experiencing severe injury (68.72% for truck drivers and 83.46% for car drivers). **(6)** When sideswipe collisions between truck-car crashes occur, 81.72% of the truck drivers result in a decrease in the probability of severe injury, possibly because trucks with larger, compared to cars, trucks with stiffer bodies, are more effective in mitigating the impact of sideswipes on their drivers. However, note that the rural roadway indicator affects the mean of the parameter density function of the sideswipe collisions indicator. Specifically, the sideswipe collisions indicator, which is a random parameter, generates, 81.72% negative betas (left of the mean) and 18.28% positive betas (right of the mean), while the rural roadway indicator, which results in heterogeneity in the means variable, has a positive sign, then the mean of the distribution will be shifted to the right, which will increase the number of positive betas and reduce the negative betas. This means that this shift in the mean will increases the mean of the sideswipe collisions indicator, making severe injuries more likely.

For the 2018 model, there is only **one** statistically significant variable as a random parameter (see Table 8). The 30-mph speed limit indicator is also a significant random parameter, with a low probability of severe injury for most observations (79.27% for truck drivers and 84.18% for car drivers).

For the 2019 model, there are **four** statistically significant variables as random parameters (see Table 8), including young truck drivers (between 26 and 45 years), middle-aged car drivers (between 46 and 65 years), middle-aged truck vehicle (between 3 and 10 years), and the 30-mph speed limit. Among them, **(1)** the young truck driver (between 26 and 45 years) indicator is significant as a normally distributed random parameter, wherein 66.06% of the observations result in a rise in the chances of suffering from a severe injury (and in a reduction in the rest 33.94%). Furthermore, the darkness with lights lit indicator affects the mean of the parameter density function of the young truck driver indicator. Specifically, the young truck driver indicator, which is a random parameter, generates, 66.06% positive betas (right of the mean) and 33.94% negative betas (left of the mean), while the darkness with lights lit indicator, which results in heterogeneity in the means variable, has a negative sign, then the mean of the distribution will be shifted to the left, which will increase the number of negative betas and reduce the positive betas. This means that this shift in the mean will decreases the mean of the young truck driver indicator, thus decreasing the likelihood of severe injuries. Truck drivers are more susceptible to fatigue when driving at night, leading to misjudged driving speeds, thereby inducing severe crashes. Therefore, to prevent exhaustion, careful consideration of the service hours for truck drivers is essential when developing nighttime dispatch plans. To that end, highly efficient street lighting over road segments with a high proportion of large trucks should be considered to improve visibility during nighttime conditions. Also, drivers should drive at a relatively low speed when driving on artificially lit roads. **(2)** The middle-aged car driver (between 46 and 65 years) indicator is significant as a normally distributed random parameter, where 98.72% of the observations decrease the probability of severe injury. Note that the mean of the middle-aged car driver indicator is affected by both the male indicator and the new car (3 years below) indicator. Specifically, the middle-aged car driver indicator, which is a random parameter, generates, 98.72% negative betas (left of the mean) and 1.28% positive betas (right of the mean), while the male indicator, which results in heterogeneity in the means variable, has a positive sign, then the mean of the distribution will be shifted to the right, which will increase the number of positive betas and reduce the negative betas. This means that this shift in the mean will increases the mean of the mean of the middle-aged car driver indicator, making severe injuries more likely. In contrast, the new car (3 years below) indicator has a negative sign, then the mean of the distribution will be shifted to the left, which will increase the number of negative betas and reduce the positive betas. This means that this shift in the mean will decreases the mean of the middle-aged car driver indicator, making severe injuries less likely. **(3)** The middle-aged truck vehicle (between 3 and 10 years) indicator is significant as a random parameter; among the observations, those that accounted for 60.01% of the total showed an increased probability of severe injury. **(4)** The 30-mph speed limit indicator is also significant as a random parameter, where among the observed cases, a majority (80.63%) exhibited a decreased likelihood of severe injury. The lower speed limit should be set for sections with high crash rates if the speed limit is over 30 mph. Note that the mean of the 30-mph speed limit indicator is affected by the weekdays and winter indicators. Specifically, the 30-mph speed limit indicator, which is a random parameter, generates, 80.63% negative betas (left of the mean) and 19.37% positive betas (right of the mean), while both the weekdays and winter indicators, which result in heterogeneity in the means variables, have a positive sign, then the mean of the distribution will be shifted to the right, which will increase the number of positive betas and reduce the negative betas. This means that this shift in the mean will increases the mean of the mean of indicator, making severe injuries more likely. Our finding seems consistent with the literature, in which the authors explained the potential reasons for the lower proportion of trucks on weekends than on weekdays (Moomen et al., 2019; Haq et al., 2020). In addition, during the winter months, low temperatures on road segments, along with snow and ice on the road, will likely result in poor pavement friction, resulting in higher injury severities.

6.2. Different effects of factors determining drivers' injury-severity

The crash injury severity and the effects of explanatory variables vary across different types of vehicles and yearly models. To that end, the following sections further explore statistically significant variables that show temporally stable elasticities. Among them, some explanatory variables have an interactive effect on the injury severity of drivers in

Table 8
Model estimation results for truck-car crashes based on the random parameter bivariate probit model with heterogeneity in means.

Variables	All years				2017				2018				2019			
	Truck drivers		Car drivers		Truck drivers		Car drivers		Truck drivers		Car drivers		Truck drivers		Car drivers	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	−1.776	−26.10	−1.491	−23.38	−2.231	−18.38	−1.901	−15.81	−1.677	−14.45	−1.434	−22.44	−0.829	−10.44	−0.746	−16.29
Driver characteristics																
Male truck driver (1 if male truck driver, 0 otherwise)	0.197	6.96			0.215	4.90			0.212	4.73			0.155	4.12		
Young truck driver (1 if truck driver age between 26 and 45 years, 0 otherwise)	0.474	11.12			0.418	6.11			0.348	4.32			0.309	4.64		
Standard deviation of parameter estimate (normally distributed) for young truck driver indicator	0.474	12.25			0.503	8.65							0.746	12.04		
Heterogeneity in the mean of random parameter: Darkness with lights lit	−0.426	−2.97											−0.432	−3.14		
Heterogeneity in the mean of random parameter: Winter	0.169	1.94														
Young car driver (1 if car driver age between 26 and 45 years, 0 otherwise)	−0.089	−2.93							−0.093	−1.73						
Middle-aged car driver (1 if car driver age between 46 and 65 years, 0 otherwise)	0.060	1.99	0.176	5.58					0.157	2.90	0.121	2.16	−0.174	−3.59		
Standard deviation of parameter estimate (normally distributed) for middle-aged car driver indicator			0.171	7.01									0.078	2.11		
Heterogeneity in the mean of random parameter: Below 3 years													−0.182	−1.75		
Heterogeneity in the mean of random parameter: Male			−0.152	−3.10									0.178	1.70		
Older truck driver (1 if truck driver age above 65 years, 0 otherwise)	0.546	12.26			0.398	6.09			0.163	1.96			0.507	6.51		
Truck driver home area type (1 if urban area, 0 otherwise)	−0.057	−1.94											−0.171	−3.55	−0.103	−2.18
Truck driver home area type (1 if small town, 0 otherwise)	0.099	2.20	0.075	1.70	0.122	1.88					0.167	2.13				
Car driver home area type (1 if small town, 0 otherwise)			0.120	2.55			0.120	1.84								
Driving dangerous from truck drivers (1 if yes, 0 otherwise)	0.400	12.84			0.289	5.65			0.292	4.90			0.196	4.51		
Driving dangerous from car drivers (1 if yes, 0 otherwise)	0.238	5.86	0.185	4.44	0.603	5.63	0.270	2.70	0.327	3.91			0.153	2.89	0.106	1.85
Vehicle characteristics																
New car vehicle (1 if the car is below 3 years, 0 otherwise)	−0.350	−7.93			−0.372	−2.79			−0.253	−3.17						
Standard deviation of parameter estimate (normally distributed) for new car vehicle indicator	0.464	11.94			0.739	11.35										
Middle-aged car vehicle (1 if the car is 3–10 years, 0 otherwise)	−0.241	−7.54	−0.059	−2.02	−0.446	−4.64			−0.099	−1.86			−0.098	−2.13	−0.078	−1.69
Standard deviation of parameter estimate (normally distributed) for middle-aged car vehicle indicator	0.332	14.01			0.838	19.05										
Middle-aged truck vehicle (1 if the truck is 3–10 years, 0 otherwise)	0.076	2.47							0.107	1.99			0.089	1.76		
Standard deviation of parameter estimate (normally distributed) for middle-aged truck vehicle indicator													0.351	10.37		
Older truck vehicle (1 if the truck is above 10 years, 0 otherwise)													0.104	1.79		
Truck manoeuvre (1 if trucks changing lane to the left prior to an accident, 0 otherwise)	0.307	7.96	0.227	5.75	0.238	3.83	0.290	4.26	0.512	4.01	0.343	2.71	0.275	2.64	0.264	2.66
Head-on collision (1 if head-on collision, 0 otherwise)	0.421	12.85	0.351	10.37	0.633	11.62	0.505	8.65	0.560	10.26	0.557	9.95	0.455	10.97	0.313	7.27
Sideswipe collision (1 if sideswipe collision, 0 otherwise)					−0.977	−7.04	0.148	2.09							0.191	3.12
Standard deviation of parameter estimate (normally distributed) for sideswipe collision indicator					1.080	15.14										
Heterogeneity in the mean of random parameter: Rural area type					0.300	2.20										

(*continued on next page*)

Table 8 (*continued*)

Variables	All years Truck drivers Coeff.	t-stat	Car drivers Coeff.	t-stat	2017 Truck drivers Coeff.	t-stat	Car drivers Coeff.	t-stat	2018 Truck drivers Coeff.	t-stat	Car drivers Coeff.	t-stat	2019 Truck drivers Coeff.	t-stat	Car drivers Coeff.	t-stat
Road characteristics																
Rural area (1 if the crash occurred in a rural, 0 otherwise)	0.155	3.88			0.214	3.62										
Standard deviation of parameter estimate (normally distributed) for rural area indicator	0.089	2.59			0.122	2.56										
Heterogeneity in the mean of random parameter: Winter	*−0.159*	*−1.88*														
The 30-mph speed limit (1 if speed limit is 30 mph, 0 otherwise)	−0.506	−11.89	−0.355	−8.81	−0.281	−2.78	−0.641	−5.86	−0.891	−6.80	−0.597	−6.93	−0.681	−6.08	−0.348	−6.75
Standard deviation of parameter estimate (normally distributed) for the 30-mph speed limit indicator	0.704	20.84			0.576	13.07	0.659	13.14	1.092	14.81	0.596	11.03	0.788	15.47		
Heterogeneity in the mean of random parameter: Weekdays													0.207	1.84		
Heterogeneity in the mean of random parameter: Winter	0.154	2.39											0.181	1.69		
Dual carriageway (1 if the accident occurred on a dual carriageway, 0 otherwise)							0.192	2.71							0.400	4.93
Auto traffic signal (1 if junction control is auto traffic signal, 0 otherwise)			−0.094	−1.65			−3.363	−5.16			−0.283	−3.01			−0.425	−5.33
Environment characteristics																
Darkness with lights unlit (1 if darkness with lights unlit, 0 otherwise)	0.200	4.59	0.268	6.05			0.155	2.30	0.191	2.61	0.321	4.30	0.635	6.25	0.387	4.94
Weekdays (1 if weekdays, 0 otherwise)					0.082	1.77			0.170	3.27						
Off-peak time (1 if crash time is off-peak time, 0 otherwise)															0.067	1.72
ρ	0.283	15.19			0.624	23.76			0.458	14.15			0.545	20.40		

truck-car crashes, while others have a significant effect on only one party.

6.2.1. Driver characteristics

Five statistically significant driver-related variables show relative stability over time in the model estimates: male truck drivers, young truck drivers (between 26 and 45 years), old truck drivers (65 years above), truck drivers' improper actions, and car drivers' improper actions. Among them, car drivers engaging in improper actions increase their likelihood of severe injury crashes and their opponents. Another four variables, including male truck drivers, young truck drivers (between 26 and 45 years), old truck drivers (65 years above), and truck driver improper actions, are found to affect only truck drivers significantly.

Young truck drivers are often overconfident in their driving skills (Haq et al., 2022). They have a greater propensity for engaging in unsafe driving behaviors, simultaneously leading to serious and fatal injuries. As a result, it's imperative to enhance safety education for inexperienced truck drivers and, at the same time, increase the punishment for the corresponding improper driving behavior. However, some studies have also shown that serious injuries and fatal injuries are less common among young drivers in truck-car crashes due to their physical strengths and emergency response capabilities (Behnood and Mannering, 2019). Considering driving errors, inappropriate behavior by truck drivers significantly raises the chances of severe injuries among truck drivers based on the results of the model corresponding to all years, and to the models corresponding to 2017, 2018, and 2019 (with the marginal effects being 13.10%, 6.40%, 8.40%, and 7.60%, respectively), while this variable has no statistically significant impact on the injury severity of car drivers (see Table 9). In contrast, improper actions of car drivers are found to significantly increase their risk of severe injury crashes while increasing the odds of truck driver severe injuries based on the results of the model corresponding to all years, and to the models corresponding to 2017, 2018, and 2019 (with the marginal effects being 7.30%, 18.40%, 9.60%, and 4.30%, respectively). Consequently, we can conclude that in collisions between trucks and cars resulting in severe injuries, car drivers are deemed to bear greater responsibility. More enforcement and education programs for improper behaviors of car drivers should be enhanced to improve road traffic safety. Our finding seems consistent with the existing study by Haq et al. (2020).

On average, male truck drivers are shown to elevate the estimated odds of severe injuries among truck drivers by 6.60%, 8.40%, 8.20%, and 6.00%, in all years, and in three-year periods (2017–2019), respectively, compared with female drivers (see Table 9). On the one hand, due to the particularity of the truck occupation, the proportion of male drivers is more than females; On the other hand, in contrast to car drivers, truck drivers often have to cover longer distances to reach their destination, which increases the risk of fatigue driving, a significant contributor to traffic accidents. Therefore, truck drivers should ensure sufficient sleep before driving and avoid fatigue driving, and if tired when driving, they should immediately go to the nearest service area and rest to ensure safe driving. In addition, individuals aged 65 and above are at a 16% higher risk of suffering severe injuries (see Table 9). The physical function of old drivers is programmed to diminish with age. And the reaction lag is also more likely to lead to severe injury crashes. Consequently, older drivers need to periodically assess whether they still have the ability to operate a vehicle with age proficiently. Old drivers should attend regular physical check-ups and driving safety education; if failing a driving test, they could be considered to take the initiative to return their driver's license or take compulsory license suspension.

6.2.2. Vehicle characteristics

Three statistically significant vehicle-related variables show relative stability over time in the model estimates: middle-aged car (between 3 and 10 years), lane-changing behavior by trucks, and head-on collision. Among them, middle-aged car (between 3 and 10 years) decreases the

Table 9
Pseudo-elasticities result for truck-car crashes.

Variables	Pseudo-elasticities							
	All years		2017		2018		2019	
	Truck drivers	Car drivers	Truck drivers	Car drivers	Truck drivers	Car drivers	Truck drivers	Car drivers
Driver characteristics								
Male truck driver (1 if male truck driver, 0 otherwise)	0.066		0.084		0.082		0.060	
Young truck driver (1 if truck driver age between 26 and 45 years, 0 otherwise)	0.153		0.265		0.085		0.117	
Young car driver (1 if car driver age between 26 and 45 years, 0 otherwise)	−0.030				−0.027			
Middle-aged car driver (1 if car driver age between 46 and 65 years, 0 otherwise)	0.001	0.082			0.031	0.021	−0.067	
Older truck driver (1 if truck driver age above 65 years, 0 otherwise)	0.161		0.160		0.156		0.161	
Truck driver home area type (1 if urban area, 0 otherwise)	−0.015		0.048				−0.047	−0.019
Truck driver home area type (1 if small town, 0 otherwise)	0.028	0.018				0.023		
Car driver home area type (1 if small town, 0 otherwise)		0.051		0.044				
Driving dangerous from truck drivers (1 if yes, 0 otherwise)	0.131		0.064		0.084		0.076	
Driving dangerous from car drivers (1 if yes, 0 otherwise)	0.073	0.043	0.184	0.024	0.096		0.043	0.017
Vehicle characteristics								
New car vehicle (1 if the car is below 3 years, 0 otherwise)	−0.087		−0.140		−0.071			
Middle-aged car vehicle (1 if the car is 3–10 years, 0 otherwise)	−0.047	−0.008	−0.173		−0.029		−0.025	−0.015
Middle-aged truck vehicle (1 if the truck is 3–10 years, 0 otherwise)	0.027				0.031		0.020	
Older truck vehicle (1 if the truck is above 10 years, 0 otherwise)							0.043	
Truck manoeuvre (1 if trucks changing lane to the left prior to an accident, 0 otherwise)	0.081	0.051	0.032	0.062	0.119	0.037	0.066	0.059
Head-on collision (1 if head-on collision, 0 otherwise)	0.116	0.082	0.142	0.057	0.101	0.098	0.126	0.048
Sideswipe collision (1 if sideswipe collision, 0 otherwise)			−0.219	0.026				0.072
Road characteristics								
Rural area (1 if the crash occurred in a rural, 0 otherwise)	0.058		0.155					
The 30-mph speed limit (1 if speed limit is 30 mph, 0 otherwise)	−0.163	−0.074	−0.060	−0.168	−0.195	−0.338	−0.197	−0.039
Dual carriageway (1 if the accident occurred on a dual carriageway, 0 otherwise)				0.066				0.061
Auto traffic signal (1 if junction control is auto traffic signal, 0 otherwise)		−0.031		−0.309		−0.058		−0.096
Environment characteristics								
Darkness with lights unlit (1 if darkness with lights unlit, 0 otherwise)	0.057	0.069		0.045	0.021	0.038	0.185	0.063
Weekdays (1 if weekdays, 0 otherwise)			0.032		0.058			
Off-peak time (1 if crash time is off-peak time, 0 otherwise)								0.006

injury severity of car drivers. Another two variables, including truck changing lane behavior and head-on collision, significantly affect the injury severity of both drivers involving truck-car crashes.

Lane changing by the truck indicator significantly increases the probability of serious injury and fatal injury crashes for both car and truck drivers. Due to the large size of trucks, there is a blind-vision zone when changing or turning, leading to serious injury crashes. Therefore, some interventions should be implemented, such as reminding the rear car to keep a safe distance or increasing the back view of the truck driver through advanced equipment with V2V (Vehicle to Vehicle) communication. Middle-aged cars (between 3 and 10 years) reduce the probability of severe injury for cars drivers. It is recommended that vehicles need regular maintenance (3–10 years) and reach a longer service life (more than 10 years) to consider scrap processing and replace the new car/truck to get safer driving.

Notably, we find that head-on collisions elevate the estimated odds of severe injuries for both car and truck drivers in truck-car crashes. Trucks are generally larger and heavier in weight, generating higher kinetic energy in head-on collisions with other vehicles. To prevent head-on collisions between passenger cars and heavy trucks, road planning departments must take into account specific design factors for undivided roads with a high volume of truck traffic. In addition, the autonomous emergency braking (AEB) system or airbag is advised to fit in vehicles, and drivers must be belted to reduce the injury severity resulting from accidents.

6.2.3. *Roadway characteristics*

Two statistically significant road-related variables show relative stability over time in the model estimates: the 30-mph speed limit and the presence of signalized crossings. Among them, the 30-mph speed limit significantly impacts the severity of injuries sustained by drivers of both cars and trucks. While the presence of signalized crossings significantly affects the severity of injuries suffered by drivers of cars.

Drivers of cars and trucks are less likely to experience severe injuries when a 30-mph speed limit indicator is present. This is a straightforward and intuitive finding, which is supported by previous research indicating that higher speed limits are linked to more severe crashes involving trucks (Osman et al., 2016; Uddin and Huynh, 2017). The lower speed limit should be set for sections with high crash rates if the speed limit is over 30 mph.

The presence of signalized crossings significantly decreases the estimated odds of car drivers' severe injuries by 3.10%, 30.90%, 5.80%, and 9.60% in all years, and in three years (2017–2019), respectively (see Table 9). However, the indicator is not significant in the truck driver case. Compared with truck drivers, car drivers are more likely to take improper actions (such as speeding or overtaking) at unsigned crossings, increasing the probability of severe crashes. Thus, drivers should strictly follow traffic rules (such as no speeding and no unnecessary overtaking) when driving a car. In addition, drivers should slow down and thoroughly observe the surrounding traffic conditions before entering the unsigned crossing. And traffic lights should be placed at unsigned intersections as traffic flow increases.

6.2.4. *Environmental characteristics*

One statistically significant environment-related variables show relative stability over time in the model estimates: darkness with lights unlit. The indicator that the darkness with lights unlit significantly affects the injury severity of both car and truck drivers.

The indicator that the darkness with lights unlit significantly increases the estimated odds of car and truck drivers' severe injuries in three years (2017–2019). The perception and response ability could be weakened during nighttime due to human physiological limits. This result can be attributed to the reduced visibility in darkness, which makes the drivers' perception of the external environment unclear, thus reducing their emergency response capabilities and inducing severe crashes. In this context, the illumination systems should be effectively deployed in road sections frequently used by drivers to prevent them from having severe accidents at night. In addition, more roadside facilities or lighting systems would be set up.

To that end, regarding the existing truck-car crashes safety problems, we attempt to put forward optimization suggestions based on the findings of this study, which is described in Table 10. These suggestions are beneficial for transportation agencies in considering alternatives. It is noted that more truck-car crash datasets should be included considered to make sure the accuracy of the strategies when transportation agencies will make a policy decision.

↑: Indicates an increase in the estimated likelihood for severe injuries; ↓: Indicates a decrease in the estimated likelihood for severe injuries.

Table 10
Appropriate strategies based on such findings.

Variables	Car-driver	Truck-driver	Guidelines
Interactive effect			
Car drivers' improper actions	↑	↑	More enforcement and education programs for improper behaviors of car drivers should be enhanced to improve road traffic safety.
Lane changing by truck	↑	↑	Advanced equipment with V2V (Vehicle to Vehicle) communication may be applied to remind the rear car to keep a safe distance.
Single effect on truck-driver			
Male truck drivers		↑	Male truck drivers should avoid fatigue driving.
Young truck drivers (between 26 and 45 years)		↑	More enforcement and education programs for young truck drivers should be enhanced.
Old truck drivers (65 years above)		↑	Older drivers need to periodically assess whether they still have the ability to operate a vehicle with age proficiently.
Truck drivers' improper actions		↑	More enforcement and education programs for improper behaviors of truck drivers should be enhanced to reduce the crash risk.
Single effect on car-driver			
Middle-aged car (between 3 and 10 years)	↓		Cars with longer service life (>10 years) are advised to be replaced by new cars early.
Unsigned crossings	↑		Drivers should slow down and thoroughly observe the surrounding traffic conditions before entering the unsigned crossing. And traffic lights should be placed at unsigned intersections as traffic flow increases.
Consistent effect			
The 30-mph speed limit	↓	↓	The lower speed limit should be set for sections with high crash rates if the speed limit is over 30 mph.
Darkness with lights unlit	↑	↑	More roadside facilities or lighting systems would be set up.
Head-on collision	↑	↑	The autonomous emergency braking (AEB) system or airbag is advised to fit in vehicles, and drivers must be belted to reduce the injury severity.

7. Conclusions

Using truck-car crash data from 2017 to 2019 in the UK, this study explored the driver-injury severity using a random parameter bivariate probit model with heterogeneity in means (RPBPHM). The estimated models identified various driver-, vehicle-, road-, and environmental-related characteristics that influence the severity of injuries sustained in crashes. The main conclusions are summarized as follows:

(1) The RPBPHM model provided a better statistical model fit by accommodating variations of explanatory factors and factors that affect the means of the parameter density functions of the random parameters. It also allows us to identify additional factors that may play a role in determining a parameter's actual effect on injury severity. In addition, temporal instability tests indicated that some variables still present relative temporal stability, indicating their importance in the development of long-term strategies to improve traffic safety.

(2) More importantly, the effects of the explanatory factors showing relatively temporal stability vary across different types of vehicle crashes (see Table 10). Firstly, two explanatory variables, including car driver improper actions and lane changing by trucks, have a significant interactive effect on the severity of injuries sustained by drivers involved collisions between trucks and cars. Secondly, four explanatory variables, including male truck drivers, young truck drivers, older truck drivers, and truck drivers' improper actions elevate the estimated odds of only truck drivers; while older car and unsignalized crossing increase the possibility of injury severity of only car drivers. Finally, due to shared unobserved crash-specific factors, three explanatory variables, including the 30-mph speed limit, dark no lights, and head-on collision, significantly affect the severity of injuries sustained by drivers involved in collisions between trucks and cars.

The findings from this analysis also offer a number of practical implications. Based on such findings, we conclude that **(1)** As for drivers, the reinforcement and enhancement of education programs and enforcement measures for young drivers need to be prioritized. And more enforcement for improper behaviors of drivers should be enhanced to improve road traffic safety. Older drivers need to periodically assess whether they still have the ability to operate a vehicle proficiently with age. Male truck drivers should schedule their time rationally and avoid fatigued driving. **(2)** As for vehicles, it is recommended that vehicles with longer service life (more than 10 years) are advised to be scrapped early. Advanced equipment with V2V (Vehicle to Vehicle) communication may be applied to remind the rear car to keep a safe distance or increase the back view of the truck driver. The autonomous emergency braking (AEB) system or side airbag is advised to fit in vehicles, especially cars, thus lowering the risk of head-on accidents. **(3)** As for special external environments, the lower speed limit should be set with high crash rates. In addition, more roadside facilities or lighting systems would be set up.

This study also has some limitations. Firstly, due to the lack of no injury in original datasets, this paper only analyzed crashes resulting in injuries so that more comprehensive data can be obtained for further research. Another research avenue is to investigate crashes involving additional types of vehicles in truck-involved crashes (such as truck-truck and truck-SUV/Pickup), which will provide a more comprehensive overview of the differences among crash-injury severities involving various vehicle types.

CRediT authorship contribution statement

Dongdong Song: Conceptualization, Formal analysis, Methodology, Project administration, Validation, Writing – original draft, Writing – review & editing. **Xiaobao Yang:** Conceptualization, Funding acquisition, Resources, Supervision, Writing – review & editing. **Yitao Yang:** Formal analysis, Resources, Visualization, Writing – original draft.

Pengfei Cui: Conceptualization, Data curation, Writing – review & editing. **Guangyu Zhu:** Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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