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REVIEW ARTICLE

A comparative analysis of factors affecting injury severity in speeding-related crashes on rural and urban roads

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ABSTRACT

Speeding related-crashes have caused numerous fatalities and become a worldwide health problem. This study aims at investigating the factors affecting injury severity in speeding-related crashes, considering the spatial heterogeneity on rural and urban roads. The data on speeding-related crashes were extracted from the Crash Report Sampling System (CRSS) between 2018 to 2020, including information about the characteristics of drivers, vehicles, crashes, roads, and the environment. Two separate correlated random parameter order probit models with heterogeneity in means (CRPOPHM) were established for speeding-related crashes on rural and urban roads, and the plausibility of separately modelling injury severity was tested by a set of LR tests. The model results showed that some factors were significant in both models, while others were significant in only one particular model. For example, heavy trucks and weekends are significant in the rural model; and young drivers, rear-end crashes, speed limits, and nights with lit roads are significant in the urban model. The results of correlations and heterogeneity in means of random parameters of the two models also showed some similarities and differences for speeding-related crashes on rural and urban roads. Based on these results, some policy recommendations are proposed to mitigate the injury severity of speeding-related crashes.

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KEYWORDS
Injury severity; speeding-related crashes; rural and urban roads; CROPOHM models; correlations; heterogeneity in means

1. Introduction

Speeding is one of the major contributors to motor vehicle fatalities and has been recognised as a worldwide public health problem for more than two decades. Research indicated that speeding behaviour tends to increase the risk of crashes and affects crash severity [1, 2]. According to National Highway Traffic Safety Administration (NHTSA) data, 11,258 people were killed by speeding-related crashes in 2020, a 17% increase in fatalities compared to 2019 [3]. In New Zealand, the Ministry of Transport stated that nearly 27% of fatal injuries were caused by speeding-related crashes between 2017 and 2019 [4]. In two Australian states, Queensland and New South Wales, fatalities related to driver speeding accounted for 20.4% and 39.0% respectively in 2018 [5]. Similar trends have been observed internationally, with a recent study by Pires et al. [6] finding that high over-speeding rates were reported in Europe (61.5%), Africa (51.2%), and Asia (46.4%), which further contributed to high crash rates. Therefore, it is important to identify the factors that affect the injury severity of speeding-related crashes, and to develop countermeasures and policies that are specifically designed to improve traffic safety.

Nevertheless, the differences in the overall environment between rural and urban areas may lead to different effects of factors on crashes [7]. For instance, rural roads include few safety facilities and a low level of transport services [8], and most intersections along rural roads are unsignalised due to the lower traffic volume [9]. These features usually represent potential hazards, such as frequent speeding, and already pose additional safety problems on rural roads [10]. Meanwhile, urban areas are characterised by more intensive development than rural areas (Adanu et al. 2022), thus resulting in different traffic mix and driving behaviours. Besides, urban roads are often accompanied by frequent traffic congestion, more drunk driving and night driving, which promote more speeding behaviours and serious crashes [11, 12]. A number of papers have been conducted to investigate the differences in the factors influencing the severity of crash in rural and urban areas [2, 13–15]. Given that vehicle speed varies with road conditions, the difference between urban and rural road environments inevitably affects speeding in different aspects, implying the necessity of a separate analysis of crash-affecting factors. Overall, the above facts reveal that there is an urgent need to identify the factors affecting speeding-related crashes while considering the potential difference between rural and urban roads, hence proposing effective countermeasures to mitigate the injury severity of such crashes.

To our knowledge, there have been no studies that specifically address the differences in speeding-related crash severity occurring on urban and rural roads. The objectives

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of this study are (i) to explore differences in factors contributing to speeding related crash severity on urban and rural road; (ii) to construct the CRPOPHM model capturing the unobserved heterogeneity; (iii) develop strategies to improve traffic safety. The rest of this paper is organised as follows: Section 2 presents the technical literature about factors that affect speeding-related crashes; Section 3 introduced the employed dataset; Section 4 described the process of methodology design and Section 5 presented the models' results and discussions; Finally, the policy recommendations and conclusions are summarised in Section 6 and 7.

2. Literature review

Normally, a speeding-related crash is defined as a driver who is involved in a crash due to exceeding the posted limit, driving too fast for conditions, or committing a speeding-related offence. Since driver speeding always causes serious consequences, numerous studies regarded speeding as an influencing factor and measured its effect on crash injury severity. For example, Wang et al. [16] compared the crash data from five countries (i.e. USA, UK, France, China, and Germany) and pointed out that speeding is the primary cause of the most devastating crashes, the case of fatality rate caused by speeding is 0.345, much higher than the average rate (0.243) caused by other factors. Gong and Fan [17] studied a range of factors significantly related to single-vehicle run-off-road crashes, and their results showed that speeding can lead to an eight-fold increase in the probability of injury or fatal crashes, second only to drunk driving; Wang and Prato [18] found that speeding increases the probability of fatal crashes by 4.4% with a prevalence equal to 21.3% among truck drivers. Rusli et al. [10] proved that speeding is the most dangerous behaviour while driving on downgrade sections, and this behaviour dramatically increased the probability of crashes by 45%.

Some studies set their sights on the reasons drivers trigger speeding behaviours. In this regard, Tseng et al. [19] found that truck drivers' speeding offences are significantly associated with their age, education, sleep quality, and driving status. Hu and Chen [11] confirmed that speeding was caused by drivers' fatigue and frustration; Nguyen et al. [20] revealed that some drivers speed to satisfy their situational needs such as self-expression, social acceptance, competence, or arousal. Zhang et al. [21] analysed 11,055 speeding violations and their results showed that human factors (e.g. novice and male drivers), vehicle factors (e.g. goods vehicles, private vehicles, and commercial operation), and environmental factors (e.g. street-light conditions, visibility level, and the time of day or years) are significantly contributed to speeding behaviours. Moreover, factors related to psychosocial (e.g. higher sensation seeking, substance use, tolerance of deviance) and personality (susceptibility to peer pressure, number of risky friends, perceived risk, increased over time) were also proved to be important predictors of speeding [22].

Given the excessive casualties and huge financial losses caused by speed-related crashes, enforcement operations such as speeding fines, speed cameras, speed limit traffic signs, etc. have been carried out to prevent frequent speeding behaviours [23]. However, the actual effectiveness of these measures may vary depending on the rural and urban roads because the potential risk factors are different. In addition to analysing the factors influencing speeding-related crashes, the importance of providing more reliable conclusions by comparing the injury severities and the associated contributors at the different spatial levels should also be highlighted. Furthermore, rural roads and urban roads are acknowledged as two major contributors to affecting injury severity of crashes in a large body of previous studies [8, 10, 11, 24], while several studies demonstrated that the influencing factors of specific crashes occurred on rural and urban roads are quite different [25]. At present, only a few studies have specifically explored the factors affecting speeding-related crashes [26–28], while none of them particularly consider the different circumstances on rural and urban roads.

As for the injury severity model, ordered response models are suitable because the injury severity is an ordinal scale variable in nature. Given the difficulty of including the full range of factors affecting the injury severity of crashes in the modelling process, which may cause unobserved heterogeneity, the random parameters method was applied to the ordered model framework in previous studies [29]. However, some scholars found that the traditional random parameter-ordered models still have two main shortcomings [30]: first, it estimates random parameters individually and independently; second, it assumes the same random parameter means across all individuals. Ignoring the correlations and heterogeneity means of random parameters may result in biased coefficient estimates [31]. Recently, a new theoretical framework, the correlated random parameter ordered probit model with heterogeneity in means (CRPOPHM), has been proposed to address the problems above and has demonstrated its superiority in many studies [25, 30, 32].

In conclusion, the aims of this study are to (1) explore the significant influencing factors of speeding-related crashes on rural and urban roads; (2) apply the CRPOPHM model to capture the correlations and heterogeneity in means of random parameters and gain a deeper understanding of the causes of crashes; (3) compare the similarities and differences for crashes occurred in different areas so that more precise countermeasures can be proposed.

3. Data description

The data used in this study was obtained from the Crash Report Sampling System (CRSS) between 2018 to 2020. The CRSS draws high-quality data at random from 60 selected areas across the United States, where there are approximately 5 to 6 million police-reported crash samples each year. CRSS focuses on those crashes that are of most concern to the highway safety community and the general public, which include vast quantities of information about the characteristics of drivers, vehicles, crashes, roads, environment, etc. The system also records the detailed behaviours of each driver before being involved in a crash, which is helpful to screen out speeding-related crashes.

To fulfil the purpose of this study, the selected data must meet three criteria: (1) at least one of the drivers involved in a crash performed speeding behaviour; (2) the vehicles involved in the crashes were motor vehicles or motorcycles; (3) the crashes occurred on rural or urban roads; (4) no missing values, and the records of 'unknown' or 'not reported' were also not allowed. In this precondition, a total of 2,932 and 6,913 speeding-related crashes that occurred on rural and urban roads, respectively, were extracted from the original data of the CRSS. Note that the injury severity of each crash was measured by a KABCO scale (i.e. K = fatal injury, A = suspected serious injury, B = suspected minor injury, C = possible injury, and O = no apparent injury). Accordingly, the frequency and percentage of the crashes divided by the KOABC scale were shown in Figure 1.

Table 1 presents descriptive statistics for the explanatory variables related to characteristics of drivers, vehicles, crashes, roads, and environment based on the data of rural and urban speeding-related crashes. Note that all variables are treated as dummy variables. The chi-square test was used to explore the protentional difference between the two groups of data. The results implied that there are significant differences in most variables for speeding-related crashes on rural and urban roads, and the subsequent analysis may consider separate models based on these two sets of data.

4. Methodology

4.1. Model construction

In this section, the theoretical framework of the CRPOPHM model is introduced. Initially, the speeding-related crash severity is assumed to be represented by a latent variable Y_i^*, the linear relationship between Y_i^* and a set of explanatory variables X_i in observation i can be expressed as follows [33–35]:

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

where β_i is a vector of parameters to be estimated, ε_i is a random error term and assumed to be normally distributed, Y_i^* denotes the i-th crash severity, X_i represents the explanatory variables for the i-th crash, and all explanatory variables are defined in Table 1. However, in actual engineering practice, crash severity is recorded as the KABCO scale. KABCO scales can be converted to categorical variables, where K is represented by 4, A is represented by 3, B is represented by 2, C is represented by 1, O is represented by 0. The association of Y_i^* and the observed injury severity y_i can be described as:

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

where j denotes the injury severity determined by the KABCO scale, μ_{ij} represents the estimated thresholds while $u_{i,0}$ was set to $-\infty$ and $u_{i,4}$ was set to $+\infty$. The probability of the crash i being j-th injury severity is formulated as:

$$\begin{cases} P(y=0) = \Phi(-\beta_i X_i) \\ P(y=1) = \Phi(u_{i,1} - \beta_i X_i) - \Phi(-\beta_i X_i) \\ P(y=2) = \Phi(u_{i,2} - \beta_i X_i) - \Phi(u_{i,1} - \beta_i X_i) \\ P(y=3) = \Phi(u_{i,3} - \beta_i X_i) - \Phi(u_{i,2} - \beta_i X_i) \\ P(y=4) = 1 - \Phi(u_{i,3} - \beta_i X_i) \end{cases} \tag{3}$$

where $\Phi(*)$ represents the standard normal distribution cumulative function. In order to capture the effect of unobserved factors varying across the crash observations, the random parameters probit model is developed, and partial parameters β_i are relaxed, set to follow the normally distributed, as follows [36]:

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

where β denotes the constant term representing the mean value of the normal distribution, ζ_i is the normally distributed term with mean = 0 and variance σ^2. In order to capture the correlations and the heterogeneity in means among random parameters, Equation (4) can be extended further as follows:

$$\beta_i = \beta + \lambda Z_i + \Gamma\omega \tag{5}$$

where β is the mean value of the random parameters for all observations, Z_i represents the vector of explanatory variables affecting the value of β_i, λ is the estimated parameter corresponding to Z_i, the term λZ_i is used to capture heterogeneity in means of random parameters, ω denotes a

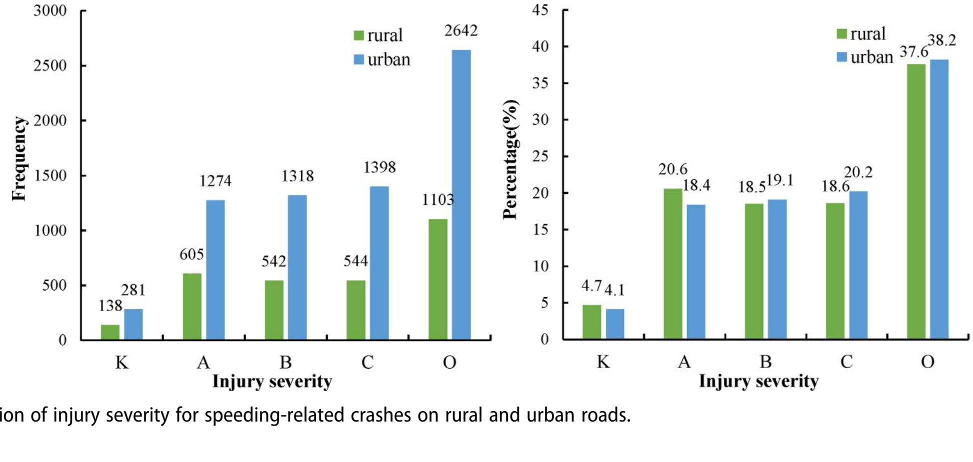

Figure 1. The distribution of injury severity for speeding-related crashes on rural and urban roads.

Table 1. Descriptive statistics of the variables used in the estimations.

	Rural		Urban		
Variable	Mean	S.D.	Mean	S.D.	Chi-square statistics
Drivers and vehicle characteristics					
Male drivers (1 if yes; 0 otherwise)	0.692	0.462	0.690	0.461	0.21
Young drivers (1 if age $\leq$ 20 years; 0 otherwise)	0.202	0.401	0.186	0.389	3.30*
Older drivers (1 if age $\geq$ 60 years; 0 otherwise)	0.078	0.268	0.071	0.257	1.26
Alcohol involved (1 if the driver is drunk; 0 otherwise)	0.170	0.376	0.134	0.341	21.45***
Speeding violation (1 if exceeded speed limit, 0 too fast for conditions)	0.211	0.408	0.174	0.380	18.33***
Model year (1 if the speeding vehicle's model $\geq$ 10 years; 0 otherwise)	0.571	0.495	0.508	0.500	32.19***
Light truck (1 if the speeding vehicle is a light truck; 0 otherwise)	0.372	0.484	0.344	0.475	7.15***
Heavy truck (1 if the speeding vehicle is a heavy truck; 0 otherwise)	0.031	0.174	0.022	0.147	7.51***
Motorcycle (1 if the speeding vehicle is a motorcycle; 0 otherwise)	0.085	0.279	0.092	0.290	1.42
Crash characteristics					
Single vehicle crash (1 if yes; 0 otherwise)	0.576	0.494	0.364	0.481	378.42***
Two vehicles crash (1 if yes; 0 otherwise)	0.259	0.480	0.480	0.500	121.75***
Rear-end crash (1 if yes; 0 otherwise)	0.240	0.427	0.428	0.495	310.92***
Head-on crash (1 if yes; 0 otherwise)	0.025	0.156	0.021	0.142	1.83
Angle crash (1 if yes; 0 otherwise)	0.075	0.263	0.086	0.281	3.47*
Sideswipe crash (1 if yes; 0 otherwise)	0.038	0.192	0.047	0.211	3.43*
Rollover crash (1 if yes; 0 otherwise)	0.174	0.379	0.089	0.284	149.82***
Road characteristics					
Interstate (1 if the crash occurs on interstate highways; 0 otherwise)	0.155	0.361	0.182	0.386	11.15***
Intersection (1 if the crash occurs at intersections; 0 otherwise)	0.233	0.423	0.251	0.434	3.80**
Uphill (1 if the crash occurs on uphill roads; 0 otherwise)	0.053	0.224	0.032	0.176	24.47***
Downhill (1 if the crash occurs on uphill roads; 0 otherwise)	0.107	0.309	0.056	0.229	81.49***
Speed limit (1 if the speed limit $\geq$ 60 km/h; 0 otherwise)	0.215	0.411	0.224	0.417	0.92
Traffic signal control (1 if yes; 0 otherwise)	0.179	0.383	0.203	0.402	7.64***
Environmental characteristics					
Dark (1 if the night without light; 0 otherwise)	0.248	0.432	0.145	0.352	152.32***
Lighted (1 if the night with light; 0 otherwise)	0.126	0.332	0.208	0.406	93.63***
Dawn/Dusk (1 if a crash occurs during dawn or dusk, 0 otherwise)	0.017	0.131	0.022	0.146	2.10
Weekend (1 if a crash occurs during the weekend, 0 otherwise)	0.294	0.456	0.303	0.46	0.74
Weather (1 if the weather is bad, i.e. rain, snow, or fog, 0 otherwise)	0.413	0.493	0.335	0.472	54.33***

Note: '*', '**', and '***', respectively, represent that the variable is significant at 90%, 95% and 99% confidence intervals.

random term with zero mean, Γ denotes the Cholesky matrix used to estimate the covariance matrix of random parameters, defined in Equation (6):

$$Var(\beta_i|\upsilon_i) = \Gamma\Gamma^{'} \tag{6}$$

In the uncorrelated random parameter order probit model, Γ is defined as a diagonal matrix, and the variance of β_i is simply σ^2 [2, 32]. To relax the hypothetical restriction, a more generalised formulation the of Cholesky matrix, Γ, is defined, with the off-diagonal elements taking non-zero values, and is shown in Equation (7):

$$\Gamma = \begin{bmatrix} \sigma_{1,1} & \sigma_{1,2} & \cdots & \sigma_{1,p-1} & \sigma_{1,p} \\ \sigma_{2,1} & \sigma_{2,2} & \cdots & \sigma_{2,p-1} & \sigma_{2,p} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \sigma_{p-1,1} & \sigma_{p-1,2} & \cdots & \sigma_{p-1,p-1} & \sigma_{p-1,p} \\ \sigma_{p,1} & \sigma_{p,2} & \cdots & \sigma_{p,p-1} & \sigma_{p,p} \end{bmatrix} \tag{7}$$

where p is the number of the random parameters in the model, $\sigma_{k,j}(1 \leq k \leq p, 1 \leq j \leq p)$ represents the elements of the Cholesky matrix. The diagonal and off-diagonal elements of the kth random parameter in V are $(\sigma_{k,k})$ and $(\sigma_{p,p\text{-}1}, \sigma_{p,p\text{-}2}, \ldots, \sigma_{p,k})$, respectively, so the standard deviation of this random parameter σ_p can be calculated as [37]:

$$\sigma_k = \sqrt{\sigma_{p,p}^2 + \sigma_{p,p-1}^2 + \sigma_{p,p-2}^2 + \cdots + \sigma_{p,k}^2} \tag{8}$$

After the correlations among random parameters were identified, the correlation coefficient between two correlated random parameters X_{k1} and X_{k2} is derived as follows:

$$Corr[X_{k1}, X_{k2}] = \frac{Cov[X_{k1}, X_{k2}]}{\sigma_{k1}\sigma_{k2}} \tag{9}$$

where $Cov[X_{k1}, X_{k2}]$ the covariance of the X_{k1} and X_{k2}, σ_{p1} and σ_{p2} can be calculated *via* Equation (8). Note that all the parameters were estimated using a simulated maximum likelihood estimation with 1000 Halton draws, and a stepwise method was used to select significant variables.

To measure the impact of changing a categorical explanatory variable from '0' to '1' on the probabilities of the outcome variable, the average marginal effects across all the crash observations were computed, as shown in Equation (10) [35, 37, 38]:

$$\frac{P(y=j)}{\partial x} = \left[\Phi(\mu_{i,j-1} - \beta_i X_i) - \Phi(\mu_{i,j} - \beta_i X_i)\right]\beta \tag{10}$$

4.2. Model evaluation methods

Several goodness-of-fit indicators including Log-likelihood at convergence ($LL(\beta)$), Akaike Information Criterion (AIC), and McFadden R^2, and a series of Chi-square (χ^2) tests were used to confirm the priority of the CRPOPHM model. The relevant formulae are shown below:

$$LL(\beta) = \sum_{i=1}^{N}\sum_{j=0}^{J}\delta_{ji}LN\left[P(y=j)\right] \tag{11}$$

$$AIC = -2 \times [LL(\beta) + K] \tag{12}$$

$$R^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{13}$$

$$\chi^2 = -2[LL(\beta_{m1}) - LL(\beta_{m2})] \tag{14}$$

where N is the number of crash observations, K is the number of estimated parameters, $LL(0)$ represents the Log-likelihood at zero, $LL(\beta_{m1})$ and $LL(\beta_{m2})$ are the Log-likelihood at the convergence of the two models to be compared.

4.3. Likelihood ratio (LR) tests

Two LR tests were used to validate (1) the reasonableness of dividing the crash sample into urban and rural areas for separate analysis; (2) the transferability of the parameter estimates between the two sub-models (i.e. rural and urban model). The first test is conducted between the model based on the full crash sample and the two sub-models; hence, the LR_f is given as:

$$LR_f = -2\left[LL(\beta_f) - LL(\beta_{n1}) - LL(\beta_{n2})\right] \tag{15}$$

The test statistic of LR_f is supposed to follow a χ^2 distribution and the degree of freedom is equal to the number of parameters estimated in the full model minus the total number of parameters estimated in the two sub-models. $LL(\beta_f)$, $LL(\beta_{n1})$, and $LL(\beta_{n2})$ are the Log-likelihood at the convergence of the three models. The second test is conducted between the two sub-models with two test statistics LR_{n1n2} and LR_{n2n1}, which are given as:

$$LR_{n1n2} = -2[LL(\beta_{n1n2}) - LL(\beta_{n2})] \tag{16}$$

$$LR_{n2n1} = -2[LL(\beta_{n2n1}) - LL(\beta_{n1})] \tag{17}$$

where $LL(\beta_{n1n2})$ is the log-likelihood at the convergence of the rural model with significant parameters using the urban sample, and $LL(\beta_{n2n1})$ is the log-likelihood at the convergence of the urban model with significant parameters using the rural sample data. Similarly, LR_{n1n2} and LR_{n2n1} are supposed to follow χ^2 distribution with a degree of freedom equal to the difference in the number of significant parameters between the models used in Equation (13) and Equation (14), respectively.

5. Results and discussions

5.1. The selected injury severity model

In this study, four types of injury severity models were established for rural and urban speeding-related crashes, respectively, and the results of the goodness-of-fit indicators and χ^2 test among these models are shown in Table 2. The CRPOPHM models for both crash samples obtained the smallest $|LL(\beta)|$ and AIC values, and the highest McFadden R^2 values than other types of models, indicating a better fit for the CRPOPHM models. The results of the χ^2 tests also demonstrated the superiority of the two CRPOPHM models at a confidence level above 99.0%. Meanwhile, the first LR test obtained LR_f equals 149.8 with 36 degrees of freedom, indicating that the null hypothesis of using a full crash sample is rejected at the confidence level of 99.9%. The second group of LR tests obtained LR_{n1n2} equals 17.6 with 6 degrees of freedom and LR_{n2n1} equals 15.5 with 5 degrees of freedom, both of which indicated that parameter estimates are not the same between the two sub-models at the confidence level of 99.0%. Therefore, the subsequent analysis is based on the results of two separated CRPOPHM models.

Table 2. Model comparison between URPOP, CRPOP, URPOPHM, and CRPOPHM.

	Rural			Urban		
Other models	URPOP	CRPOP	URPOPHM	URPOP	CRPOP	URPOPHM
K	28	36	42	22	27	38
LL(β)	−3899.8	−3899.3	−3874.3	−9151.8	−9094.3	−9076.6
DF	17	9	3	18	13	2
χ^2	37.01	36.51	11.49	86.27	28.75	11.01
LC	99.95%	99.99%	99.00%	99.99%	99.00%	99.95%
McFadden R^2	0.090	0.090	0.096	0.086	0.092	0.094
AIC	7855.6	7870.6	7832.6	18347.6	18242.6	18229.2
BM	CRPOPHM	CRPOPHM	CRPOPHM	CRPOPHM	CRPOPHM	CRPOPHM

Note: K = Number of estimated parameters, LL(β)= Log-likelihood at convergence, DF = Degree of freedom, LC = Level of confidence, BM = Better model.

Table 3 presents the coefficient estimation results of the two sub-models. Note that only the statistically significant parameters at the 90% significance level are retained in the models, and all random parameters are assumed to follow a normal distribution [30, 39]. Overall, the significant fixed parameters and random parameters are not the same between the two sub-models. In the rural model, 10 fixed parameters (i.e. older drivers, alcohol involved, etc.) and 5 random parameters (i.e. heavy truck, adverse weather, etc.) are statistically significant, and variables including 'speed limit' and 'interstate' were found to influence the mean of random parameters; In the urban model, 14 fixed parameters (i.e. older drivers, speeding violation, etc.) and 4 random parameters (i.e. single-vehicle crash, the night without light, etc.) are statistically significant, and variables including 'traffic signal control' and 'interstate' were found to influence the mean of random parameters. The information about the distribution effects and the correlations of the random parameters in the two sub-models are shown in Table 4, and the marginal effects of the significant variables for different levels of injury severity in speeding-related crashes on rural and urban roads are shown in Figure 2.

5.2. Drivers and vehicle characteristics

Driver factors such as older drivers, alcohol involved and violation of maximum speed limits are significant in both rural and urban models and increase the probability of speeding-related crashes with fatal, serious, and minor injuries. Drivers who fit the above three factors usually share features of slower immediate response and lower ability to control the vehicle [40, 41], making avoiding hazardous situations more challenging as speed-related crashes leave them with only a short reaction time. Besides, this study confirms that alcohol involvement causes the most serious injuries on rural roads, while violation of maximum speed limits causes the most serious injuries on urban roads, further demonstrating the differences in consequences of

Table 3. Model estimation of speeding-related crash severity for rural and urban samples.

	Rural		Urban	
Variable	Coefficient	t-stat	Coefficient	t-stat
Constant	0.462***	5.00	0.455***	6.73
Drivers and vehicle characteristics				
Young drivers			−0.097**	−2.18
Standard deviation			0.250***	7.22
Older drivers	0.353***	4.33	0.143***	2.68
Alcohol involved	1.002***	17.48	0.451***	10.76
Speeding violation	0.617***	11.69	0.644***	17.69
Heavy truck	−0.751***	−3.34		
Standard deviation	1.461***	8.78		
Motorcycle	1.042***	12.18	1.138***	20.37
Crash characteristics				
Single vehicle crash	−0.330***	−3.44	−0.491***	−7.19
Standard deviation	0.211***	7.42	0.734***	25.17
Two vehicles crash	−0.464***	−4.99	−0.454***	−11.79
Rear-end crash			−0.148**	−2.45
Head-on crash	1.110***	9.05	1.130***	10.33
Angle crash	0.302***	3.46	0.430***	6.07
Sideswipe crash	−0.388***	−3.13	−0.304***	−3.52
Rollover crash	0.716***	12.02	0.994***	19.74
Road characteristics				
Intersection	−0.180***	−3.18	−0.139***	−3.63
Downhill	0.166**	2.39	0.232***	3.99
Speed limit			0.160***	4.18
Environmental characteristics				
Dark	0.056*	1.92	0.255***	5.03
Standard deviation	0.473***	8.88	0.742***	18.55
Lighted	–	–	0.186***	5.35
Weather	−0.262***	−4.97	−0.104***	−2.78
Standard deviation	0.523***	12.19	0.285***	11.60
Weekend	−0.216***	−4.03		
Standard deviation	0.116***	2.65		
Heterogeneity in means				
Heavy truck: Speed limit	−0.788*	−1.93		
Heavy truck: Interstate	1.034**	2.52		
Weekend: Speed limit	0.371**	2.49		
Single vehicle crash: Speed limit	−0.432***	−2.99		
Dark: Speed limit	0.310*	1.87		
Dark: Interstate	−0.336*	−1.87	0.201**	2.03
Dark: Traffic signal control			0.364***	2.91
Single vehicle crash: Traffic signal control			0.167**	2.23
Young drivers: Interstate			−0.183*	−1.84
Weather: Interstate			−0.125*	−1.75
Weather: Traffic signal control			−0.146*	−1.91
Threshold parameters				
μ_1	0.702***	25.56	0.697***	41.26
μ_2	1.473***	38.87	1.468***	62.33
μ_3	3.003***	47.17	2.907***	72.72
Model statistics				
Number of estimated parameters	45		40	
Number of observations	2932		6913	
Log-likelihood at zero	−4286.3		−10014.7	
Log-likelihood at convergence	−3862.8		−9065.6	
McFadden R^2	0.099		0.095	
AIC	7815.5		18211.1	

Note: '*', '**', and '***', respectively, represent that the variable is significant at 90%, 95% and 99% confidence intervals.

speed-related crashes on rural and urban roads in terms of risk behaviours.

Young drivers are only significant in the urban model and performed mixed effects on injury severity. This factor increases injury severity for 34.83% of the observation and decreases the injury severity for 65.17% of the observation. In general, young drivers enjoy relatively good physical and mental performance, allowing them to avoid some emergencies or risks on the road. However, some scholars also found that young drivers are more likely to perform risky driving behaviours [42, 43], especially speeding-related behaviours [44], given that they always overestimate their driving skills. From another perspective, Erkuş and Özkan [45] reported that young drivers voluntarily engage in high-risk behaviours due to their negative attitudes towards safety, which results in their over-representation in traffic crashes. This research also indicated that excessive speeding by older drivers can escalate the crash severity, especially on rural roads. Previous studies have reported similar findings in two-vehicle crashes [46], rear-end crashes (Yuan et al. 2023d), and single-vehicle crashes [47, 48], work zone crashes [49, 50].

As for vehicle factors, this study found that motorcycles had a relatively higher probability of causing fatal and

Table 4. Random parameters correlation coefficients' matrix and their distributional splits across all samples.

	Rural					Distributional splits (%)	
Variable	Heavy truck	Weather	Dark	Weekend	Single vehicle crash	Below zero	Above zero
Heavy truck	1.000 [1.461] (8.78)					69.50	30.50
Weather	0.512 [0.312] (7.36)	1.000 [0.524] (12.19)				69.15	30.85
Dark	−0.676[-0.503] (-9.73)	0.265 [0.276] (5.35)	1.000 [0.473] (8.88)			54.78	45.22
Weekend	0.506 [0.345] (7.57)	0.896 [0.505] (10.94)	−0.325 [-0.277] (-6.18)	1.000 [0.116] (2.65)		96.86	3.14
Single vehicle crash	−0.440 [-0.330] (-8.46)	0.216 [0.386] (9.84)	0.146 [0.405] (11.27)	0.448 [0.312] (9.92)	1.000 [0.211] (7.20)	94.06	5.94
	Urban						
Variable	Single vehicle crash	Dark	Young drivers	Weather		Below zero	Above zero
Single vehicle crash	1.000 [0.734] (25.17)					74.86	25.14
Dark	−0.148 [-0.111] (-2.69)	1.000 [0.742] (18.55)				36.69	63.31
Young drivers	−0.552 [-0.203] (-5.62)	0.559 [0.177] (5.12)	1.000 [0.250] (7.22)			65.17	34.83
Weather	−0.113 [-0.064] (-2.27)	−0.597 [-0.354] (-13.43)	0.166 [0.338] (13.12)	1.000 [0.285] (11.60)		64.06	35.94

Note: the coefficients and t-stat of the correlated random parameter in the Cholesky Matrix are presented in the square brackets and parentheses, respectively.

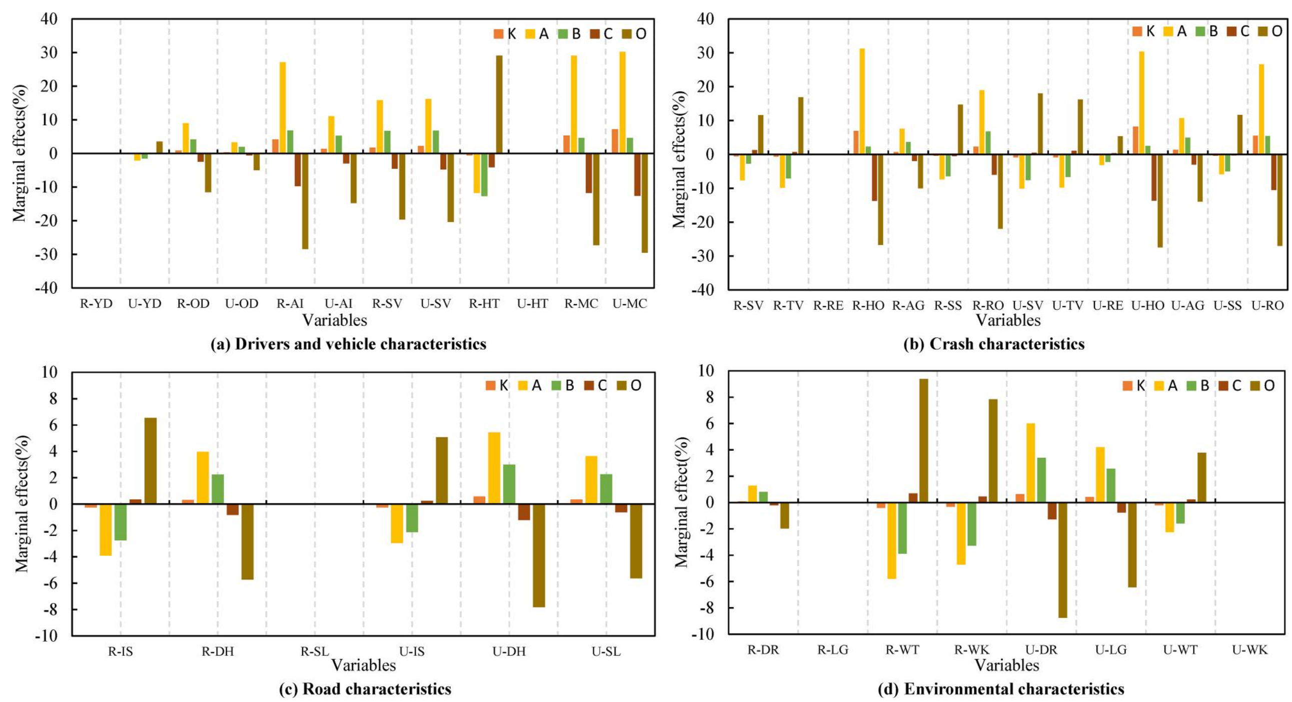

Figure 2. Marginal effect of significant variable in urban and rural speeding-related crashes.

Note: 'R-' represents rural roads; 'U-' represents urban roads; YD-young drivers; OD-older drivers; AI-alcohol involved; SV-speeding violations; HT-heavy truck; MC-motorcycle; SV-single vehicle; TV-two vehicles; RE-rear-end; HO-head-on; AG-angle; SS-sideswipe; RO-rollover; IS-intersection; DH-downhill; SL-speed limit; DR-dark; LG-lighted; WT-weather; WK-weekend.

serious injury in both models, which is consistent with many previous studies [51, 52]. Objectively speaking, motorcyclists are a relatively vulnerable group on the road and car drivers tend to ignore them while driving [53], once motorcyclists are involved in speeding-related crashes, they are often seriously injured. Nevertheless, the motorcyclists themselves were found to be more aggressive on-road and frequently involved in drink-driving, speeding, and inattentive riding [54], with a higher rate of not wearing safety equipment such as helmets [24]. Nguyen et al. [20] stated that 55 motorcyclists perceived speeding as an expression of typical manliness or as a sign of bravery and strength, so they are more likely to commit speeding to express the emotions like 'showing off', 'competitiveness', and 'thrill-seeking'.

Model results reveal that heavy trucks are only significant in the rural model. This result is understandable because most urban roads have strict restrictions on heavy trucks. On rural roads, heavy trucks were found to decrease the injury severity for most of the observations (69.50%). Truck drivers are required to go through a rigorous selection and testing process with relatively high levels of driving experience and skills, which is helpful for them to adapt to different types of road conditions [56]. However, nearly 30% of truck drivers still cause severer injuries, possibly due to the commercial attributes of this occupational group, which leads them to be regularly involved in speeding, driving while fatigued, and overloaded [18, 19], and even suffering from serious health problems [57].

5.3. Crash characteristics

In both rural and urban models, most factors related to crash characteristics play an important role in determining injury severity. Crash types including head-on crashes, angle crashes, and rollover crashes were found to increase the probability of fatal, serious, and minor injury in speeding-related crashes, which is consistent with many previous studies [29, 58, 59]. The main reason is that excessive speed forces drivers' vision to the far side of the vehicle, making it difficult for them to observe their surroundings or avoid nearby vehicles. Moreover, the findings show that rear-end crash was only significant on urban roads and increased the probability of no apparent injury. This result is consistent with the findings of Kockelman and Kweon [60] and Rusli et al. [61], which revealed that rear-end crashes are common but generally less severe in nature.

Regarding the number of vehicles involved in speed-related crashes, this study found that single- and two-vehicle crashes caused less serious consequences compared to multiple-vehicle crashes. This result is intuitive because multiple-vehicle crashes usually involve more types of vehicles (e.g. trucks and cars) with a larger number of victims. Specifically, speeding vehicles cannot slow down immediately and have a higher probability of hitting multiple objects [62]. The findings also confirmed that single crashes have mixed effects on injury severity in both rural and urban models, indicating that 5.94% and 25.14% of the observations on rural and urban roads, respectively, caused more serious consequences due to single crashes. Previous studies have pointed out that several types of single vehicles such as hitting a tree, overturning, and running off the roads are strongly associated with fatal and serious injuries [17, 29, 39], and these crashes may be more likely to occur in urban areas because of more road obstacles and complex traffic conditions.

5.4. Road characteristics

Several significant factors related to road characteristics are found in both models. In brief, intersection segments decrease the probability of fatal, serious, and minor injury, while the opposite results are obtained for downhill segments. Road intersections are usually tightly controlled (e.g. equipped with signals, videos, traffic signs, and markings, or patrolled by traffic police), which can effectively limit speeding-related behaviours or crashes. In Italy, Gariazzo et al. [63] observed that higher risks are associated with fatal and injury crashes on roads with no intersections. Similarly, based on the data collected from the Connecticut Crash Data Repository, Wang et al. [32] found a lower probability of severe crashes on both sign-controlled and signalised intersections. However, crashes on downhill segments are more likely to cause serious injuries, because these segments tend to prompt drivers to overtake or forcibly speed, as has been proved by Lee et al. [64]. Importantly, our study finds that speed limits $\geq$60km had no significant effects on the injury severity of speeding-related crashes on rural roads, and instead significantly increased the probability of serious injuries in speeding-related crashes on urban roads, indicating that a relatively high-speed limit on roads is not an effective measure in mitigating speeding by drivers, especially on urban roads.

5.5. Environmental characteristics

Previous studies have identified the complex effects of factors related to environmental characteristics on crash injury severity [30, 47, 65], and our study has yielded some similar results for speeding-related crashes on both rural and urban roads. For example, driving at night without light increases the probability of more serious injuries for 45.22% and 63.31% of the observation while causing the opposite results for 54.78% and 36.69% of the observation on rural and urban roads, respectively. Also, driving under adverse weather was found to have mixed effects on injury severity. The main reason for these phenomena is that such adverse driving conditions can on the one hand cause certain driving difficulties (e.g. difficulty in observing the surroundings, controlling the vehicle, maintaining the appropriate lane, etc.) for drivers, but can on the other hand increase the drivers' alertness and concentration in driving.

Besides, our study adds to the literature by finding that more drivers on urban roads increase injury severity than those on rural roads under the conditions of the night without light or adverse weather. One possible reason may lie in the high traffic density and mixed traffic flow conditions on urban roads compared to rural roads [11], while it has been proved that frequent traffic congestion in urban areas can significantly increase driving anger [66]. In contrast to previous research [2, 9], the current study discovered that night-time accidents on well-lit urban roads were more inclined to escalate the crash severity. One possible reason for this is that in well-lit stretches at night, drivers may be more prone to relaxation. Some scholars even found that better road conditions in cities may somewhat promote speeding behaviours [12], which explains why drivers in urban areas cause serious crashes at night on lit roads. Finally, the weekend was found to have mixed effects on injury severity of crashes on rural roads, and 3.14% of the observation increased the probability of more serious injuries. This is partly because that much of the traffic during weekends consisted of discretionary travel, which involved more drinking, speeding, and fatigued driving [67].

5.6. Heterogeneity in means of random parameters

This study found that several factors were not significantly associated with injury severity, but can indirectly influence injury severity. In the rural model, speed limits $\geq$ 60km and interstate highways resulted in significant heterogeneity in means of random parameters. These results illustrated that a speed limit helps to mitigate the injury severity for heavy truck drivers and drivers involved in single-vehicle crashes, however, it is not suitable to set relatively high-speed limits on rural roads at weekends or during night-time as it may promote more serious speeding-related crashes. It can also be witnessed that interstate highways in rural areas resulted in more serious crashes for heavy truck drivers, which is consistent with previous studies revealing that truck drivers are more likely to drive fast to complete transportation tasks on highways [18]. Interestingly, although relatively high speeds are permitted on interstate highways, drivers are more inclined to drive carefully to ensure their safety under certain conditions, such as unlit roads at night.

In the urban model, interstate highways and traffic signal control resulted in significant heterogeneity in means of random parameters. Contrary to the results of speeding-related crashes on rural roads, drivers are more likely to cause serious injuries when driving at night on unlit urban roads, again demonstrating the need for lower speed limits in urban areas, especially on highway sections. Despite the relatively high speed on interstate highways, several conditions, such as the young age of drivers or adverse weather decrease the injury severity of crashes on these roads. In addition, our study reveals that traffic signal control can increase the injury severity for speeding-related crashes at night without light or single-vehicle crashes, but can decrease the injury severity in adverse weather, these results are consistent with several previous studies, which indicated that single-vehicle crashes tend to occur on roads with lower traffic volumes [39], where speeding behaviours are more frequent, but adverse weather can instead discourage speeding to some extent [41]. Traffic signals assist in controlling the flow of traffic in different directions, however, crashes in signalised areas can be more serious once drivers fail to obey the rules [68]. When drivers are speeding, they are more likely to ignore the signal changes, and the unlit conditions at night will undoubtedly make the situation worse [69].

5.7. Correlations among random parameters

Correlations among random parameters can provide insights into the interactive effects of variables on injury severity in speeding-related crashes on rural and urban roads, as seen in Table 4. For example, on rural roads, heavy truck drivers are more likely to increase injury severity when speeding in adverse weather or on weekends, but to decrease injury severity at night without light or in single-vehicle crashes. Similarly, on urban roads, young drivers tend to increase injury severity when speeding in adverse weather but decrease injury severity of single-vehicle crashes. Most importantly, although some random parameters (i.e. adverse weather, a night without light, and single-vehicle crash) are the same in rural and urban models, their interactions are quite different. The effects of the two-by-two combination of these three variables increase the injury severity of speeding-related crashes on rural roads, but the opposite effect was obtained on urban roads. The main reason for this phenomenon may lie in the unobserved heterogeneity and unobserved characteristics are not the same between rural and urban roads, because the rural roads are naturally poorer in terms of infrastructure and maintenance with more prevalent speeding and fatigue driving compared to urban roads [17]. These results also imply that the conditions that lead drivers to a serious crash vary depending on the combinations of certain factors, and effective crash prevention strategies need to be developed to find out and address these specific combinations.

6. Policy recommendations

Some generalised recommendations can be advanced based on the findings of this study. Technical and engineering means should be used to reduce speeding-related crashes. It is important to accurately identify the locations and periods where speeding-related crashes frequently occur, and then posted speed limits in suitable areas with appropriate frequency. Specific technical upgrades should also be applied to the speed limit signs, which allow them to be networked with the road management system so that the variable speed limit signs can be changed depending on the time of day (e.g. night-time hours) or weather conditions (e.g. rain and snow). Speed-monitoring devices such as fixed and mobile speed cameras, speed-activated roadside displays, radar velocimeters, etc. can be used in combination and set in some dangerous road sections such as downhill slopes and intersections. Besides, the application of timely communication technologies (e.g. adaptive cruise control, integrated safety systems, wireless roadside beacons, etc.) should be promoted to prevent drivers from speeding.

From the perspective of the traffic management authorities, targeted policies can be formulated to improve traffic safety according to the differences between rural and urban areas respectively. This research founds that alcohol involvement leads to the most severe injuries on rural roads, whereas exceeding maximum speed limits results in the most serious injuries on urban roads. This finding suggests that enforcement of speeding should be increased on urban roads, however, the frequency of illegal Driving Under the Influence (DIU) enforcement should be increased on rural roads. Additional drunk driving crackdowns and sobriety checkpoints could be implemented on rural roads. On the interstate highways of both rural and urban roads, highly publicised sustained enforcement actives should be implemented. Considering the adverse effects of night-time conditions on injury severity, prioritising the enhancement of lighting on unlit roads, particularly in urban areas, is imperative. Implementing random police patrols during the night or in urban areas with low visibility may also contribute to a reduction in crashes related to speeding.

In addition, drivers should be made more aware of speeding behaviours. In this regard, older drivers and motorcyclists are two groups that deserve to be concerned, especially on rural roads. It is not only to restrict their speeding behaviours from a legislative perspective but also to improve their attention on driving on rural roads and to provide targeted educational programs. In addition, the education session should illustrate to drivers the dangers of speeding behaviours, making it clear when, where, and under what conditions the risk of speeding behaviours increases, preferably through the presentation of actual examples or video footage to deepen drivers' impressions of the related consequences.

7. Conclusion and limitations

This study identified the significant influencing factors of injury severity for speeding-related crashes on rural and urban roads using three years of data extracted from the CRSS dataset. The injury severity was measured by a KOABC scale, and a range of factors including driver and vehicle characteristics, crash characteristics, roadway characteristics, and environmental characteristics were investigated. After testing the plausibility of separately modelling injury severity based on rural and urban roads with a set of LR tests, two separate CRPOPHM models were established. The results showed some factors significant in both models, while others were significant in only one particular model. For example, heavy trucks and weekends are significant in the rural model; and young drivers, rear-end crashes, speed limits, and nights with lit roads are significant in the urban model. The results of correlations and heterogeneity in means of random parameters of the two models also showed some similarities and differences for speeding-related crashes on rural and urban roads. These results are helpful for traffic management to propose effective countermeasures to mitigate the injury severity of speeding-related crashes.

This study has several limitations. Firstly, this study assumed that the influencing factors of injury severity are stable over time, which may result in some unreliable conclusions. Future research could consider the temporal stability of injury severity in speeding-related crashes. Secondly, due to the location information of the crashes is not included in the CRSS data, the conclusions of this study are therefore based on the entire CRSS sample and may not apply to particular areas. However, the method used in this study can be promoted if the data in other places are available. Lastly, the data used in this study include crashes involving at least one speeding driver; however, the situation of multiple speeding drivers may be different. However, multiple speeding drivers may have different profiles. Future research could further consider situations where multiple speeding drivers are involved in a crash and compare the results with those of this study to investigate the reasons for the differences.

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References

[1] Aarts L, Van Schagen I. Driving speed and the risk of road crashes: a review. Accid Anal Prev. 2006;38(2):215–224. doi: 10.1016/j.aap.2005.07.004.

[2] Yuan R, Ding S. Fang Z,Gu X, et al. 2023a. Investigating the spatial heterogeneity of factors influencing speeding-related crash severities using correlated random parameter order models with heterogeneity-in-means. Transportation Letters-the International Journal of Transportation Research. doi:10.1080/19427867.2023.2262201

[3] National Highway Traffic Safety Administration (NHTSA). 2022. NHTSA launches new campaign to remind drivers speeding wrecks lives. 2022-7-18, Press Release. Available from: https://www.nhtsa.gov/press-releases/nhtsa-launches-new-campaign-remind-drivers-speeding-wrecks-lives.

[4] Ministry of Transport. 2019. Annual crash statistics. Available from: https://www.transport.govt.nz/statistics-and-insights/safety-annual-statistics/.

[5] Mills L, Freeman J, Truelove V, et al. Comparative judgements of crash risk and driving ability for speeding behaviours. J Safety Res. 2021;79:68–75. doi: 10.1016/j.jsr.2021.08.006.

[6] Pires C, Torfs K, Areal A, et al. Car drivers' road safety performance: a benchmark across 32 countries. IATSS Res. 2020; 44(3):166–179. doi: 10.1016/j.iatssr.2020.08.002.

[7] Wu PJ, Song L, Meng XH. Influence of built environment and roadway characteristics on the frequency of vehicle crashes caused by driver inattention: a comparison between rural roads and urban roads. J Safety Res. 2021;79:199–210. doi: 10.1016/j.jsr.2021.09.001.

[8] Sun M, Sun X, Rahman MA, et al. Modeling two-way stop-controlled intersection crashes with zero-inflated models on Louisiana rural two-lane highways. IATSS Res. 2021;45(3):303–309. doi: 10.1016/j.iatssr.2020.12.007.

[9] Chen YK, Luo RJ, King M, et al. Spatiotemporal analysis of crash severity on rural highway: a case study in Anhui, China. Accid Anal Prev. 2022;165:106538. doi: 10.1016/j.aap.2021.106538.

[10] Rusli R, Haque MM, King M, et al. Single-vehicle crashes along rural mountainous highways in Malaysia: an application of random parameters negative binomial model. Accid Anal Prev. 2017;102:153–164. doi: 10.1016/j.aap.2017.03.002.

[11] Hu SR, Chen SY. Effects of mixed traffic and elderly passengers on city bus drivers' work-related fatigue. Transp Res Part F Traffic Psychol Behav. 2019;66:485–500. doi: 10.1016/j.trf.2019.09.020.

[12] Prati G, Pietrantoni L, Fraboni F. Using data mining techniques to predict the severity of bicycle crashes. Accid Anal Prev. 2017;101:44–54. doi: 10.1016/j.aap.2017.01.008.

[13] Agyemang W, Adanu EK, Jones S. Understanding the factors that are associated with motorcycle crash severity in rural and urban areas of Ghana. J Adv Transp. 2021;2021:1–11. doi: 10.1155/2021/6336517.

[14] Islam S, Jones SL. Pedestrian at-fault crashes on rural and urban roadways in Alabama. Accid Anal Prev. 2014;72:267–276. doi: 10.1016/j.aap.2014.07.003.

[15] Khorashadi A, Niemeier D, Shankar V, et al. Differences in rural and urban driver-injury severities in accidents involving large-trucks: an exploratory analysis. Accid Anal Prev. 2005; 37(5):910–921. doi: 10.1016/j.aap.2005.04.009.

[16] Wang DY, Liu QY, Ma L, et al. Road traffic accident severity analysis: a census-based study in China. J Safety Res. 2019;70: 135–147. doi: 10.1016/j.jsr.2019.06.002.

[17] Gong LF, Fan W. Modeling single-vehicle run-off-road crash severity in rural areas: accounting for unobserved heterogeneity and age difference. Accid Anal Prev. 2017;101:124–134. doi: 10.1016/j.aap.2017.02.014.

[18] Wang YG, Prato CG. Determinants of injury severity for truck crashes on mountain expressways in China: a case-study with a partial proportional odds model. Safety Sci. 2019;117:100–107. doi: 10.1016/j.ssci.2019.04.011.

[19] Tseng C-M, Yeh M-S, Tseng L-Y, et al. A comprehensive analysis of factors leading to speeding offenses among large-truck drivers. Transp Res Part F Traffic Psychol Behav. 2016;38:171–181. doi: 10.1016/j.trf.2016.02.007.

[20] Nguyen DVM, Vu AT, Ross V, et al. Small-displacement motorcycle crashes and risky ridership in Vietnam: findings from a focus group and in-depth interview study. Safety Sci. 2022;152:105514. doi: 10.1016/j.ssci.2021.105514.

[21] Zhang G, Yau KKW, Gong X. Traffic violations in Guangdong province of China: speeding and drunk driving. Accid Anal Prev. 2014;64:30–40. doi: 10.1016/j.aap.2013.11.002.

[22] Simons-Morton BG, Ouimet MC, Chen R, et al. Peer influence predicts speeding prevalence among teenage drivers. J Safety Res. 2012;43(5–6):397–403. doi: 10.1016/j.jsr.2012.10.002.

[23] Freeman J, Kaye S-A, Truelove V, et al. Age, gender and deterrability: are younger male drivers more likely to discount the future? Accid Anal Prev. 2017;104:1–9. doi: 10.1016/j.aap.2017.03.022.

[24] Dapilah F, Guba BY, Owusu-Sekyere E. Motorcyclist characteristics and traffic behaviour in urban Northern Ghana: implications for road traffic accidents. J Transp Health. 2017;4:237–245. doi: 10.1016/j.jth.2016.03.001.

[25] Se C, Champahom T, Jomnonkwao S, et al. Empirical comparison of the effects of urban and rural crashes on motorcyclist injury severities: a correlated random parameters ordered probit approach with heterogeneity in means. Accid Anal Prev. 2021a;161:106352. doi: 10.1016/j.aap.2021.106352.

[26] Hassan HM, Shawky M, Kishta M, et al. Investigation of drivers' behavior towards speeds using crash data and self-reported questionnaire. Accid Anal Prev. 2017;98:348–358. doi: 10.1016/j.aap.2016.10.027.

[27] Høye A. Speeding and impaired driving in fatal crashes-results from in-depth investigations. Traffic Inj Prev. 2020;21(7):425–430. doi: 10.1080/15389588.2020.1775822.

[28] Liu C, Chen CL. 2009. An analysis of speeding-related crashes: definition and effects of road environmental. In: technical Report No. DOT HS 811–090. National Highway Traffic Safety Administration NHTSA, National Center for statistics and analysis.

[29] Anarkooli A, Hosseinpour M, Kardar A. Investigation of factors affecting the injury severity of single-vehicle rollover crashes: a random-effects generalized ordered probit model. Accid Anal Prev. 2017;106:399–410. doi: 10.1016/j.aap.2017.07.008.

[30] Yu M, Zheng C, Ma C, et al. The temporal stability of factors affecting driver injury severity in run-off-road crashes: a random parameters ordered probit model with heterogeneity in the means approach. Accid Anal Prev. 2020;144:105677. doi: 10.1016/j.aap.2020.105677.

[31] Washington S, Karlaftis M, Mannering FL. 2011. Statistical and econometric methods for transportation data analysis. 2nd ed. Boca Raton, FL: Chapman and Hall/CRC.

[32] Wang K, Shirani-Bidabadi N, Razaur Rahman Shaon M, et al. Correlated mixed logit modeling with heterogeneity in means for crash severity and surrogate measure with temporal instability. Accid Anal Prev. 2021;160:106332. doi: 10.1016/j.aap.2021.106332.

[33] Azimi G, Rahimi A, Asgari H, et al. Severity analysis for large truck rollover crashes using a random parameter ordered logit model. Accid Anal Prev. 2020;135:105355. doi: 10.1016/j.aap.2019.105355.

[34] Se C, Champahom T, Jomnonkwao S, et al. Motorcyclist injury severity analysis: a comparison of artificial neural networks and random parameter model with heterogeneity in means and variances. Int J Inj Contr Saf Promot. 2022;29(4):500–515. doi: 10.1080/17457300.2022.2081985.

[35] Yuan R, Gu X, Peng Z, et al. Analysis of factors affecting occupant injury severity in rear-end crashes by different struck vehicle groups: a random thresholds random parameters hierarchical ordered probit model. J Transport Saf Sec. 2023b;15(6):636–657. doi: 10.1080/19439962.2022.2098891.

[36] Wang S, Li F, Wang Z, et al. A random parameter bivariate probit model for injury severities of riders and pillion passengers in motorcycle crashes. J Transport Saf Sec. 2022;14(8):1289–1306. doi: 10.1080/19439962.2021.1916666.

[37] Jalayer M, Shabanpour R, Pour-Rouholamin M, et al. Wrong-way driving crashes: a random-parameters ordered probit analysis of injury severity. Accid Anal Prev. 2018;117:128–135. doi: 10.1016/j.aap.2018.04.019.

[38] Ding S, Abdel-Aty M, Wang D, et al. 2023. Exploratory analysis of the crash severity involving vehicles with different levels of driving automation (SAE L2-5) using multi-source data. arXiv e-prints, arXiv-2303.

[39] Li Z, Chen C, Wu Q, et al. Exploring driver injury severity patterns and causes in low visibility related single-vehicle crashes using a finite mixture random parameters model. Anal Methods Accid Res. 2018;20:1–14. doi: 10.1016/j.amar.2018.08.001.

[40] Islam M, Hernandez S. Multi-vehicle collisions involving large trucks on highways: an exploratory discrete outcome analysis. J Transp Eng. 2013;139(6):596–604. doi: 10.1061/(ASCE)TE.1943-5436.0000539.

[41] Naik B, Tung L-W, Zhao S, et al. Weather impacts on single-vehicle truck crash injury severity. J Safety Res. 2016;58:57–65. doi: 10.1016/j.jsr.2016.06.005.

[42] Rolison JJ, Hanoch Y, Wood S, et al. Risk taking differences across the adult lifespan: a question of age and domain. J Gerontol B Psychol Sci Soc Sci. 2014;69(6):870–880. doi: 10.1093/geronb/gbt081.

[43] Williams AF, Shabanova VI. Responsibility of drivers, by age and gender, for motor vehicle crash deaths. J Safety Res. 2003;34(5):527–531. doi: 10.1016/j.jsr.2003.03.001.

[44] Hassan HM, Abdel-Aty MA. Exploring the safety implications of young drivers' behavior, attitudes and perceptions. Accid Anal Prev. 2013;50:361–370. doi: 10.1016/j.aap.2012.05.003.

[45] Erkuş U, Özkan T. Young male taxi drivers and private car users on driving simulator for their self-reported driving skills and behaviors. Transp Res Part F Traffic Psychol Behav. 2019;64:70–83. doi: 10.1016/j.trf.2019.04.028.

[46] Yuan R, Gan J, Peng Z, et al. Injury severity analysis of two-vehicle crashes at unsignalized intersections using mixed logit models. International Journal of Injury Control and Safety Promotion. 2022;29(3):348–359. 10.1080/17457300.2022.2040540

[47] Se C, Champahom T, Jomnonkwao S, et al. Temporal stability of factors influencing driver-injury severities in single-vehicle crashes: a correlated random parameters with heterogeneity in means and variances approach. Anal Methods Accid Res. 2021b;32:100179. doi: 10.1016/j.amar.2021.100179.

[48] Xie Y, Zhao K, Huynh N. Analysis of driver injury severity in rural single-vehicle crashes. Accid Anal Prev. 2012;47:36–44. doi: 10.1016/j.aap.2011.12.012.

[49] Chen H, Cao L, Logan DB. Analysis of risk factors affecting the severity of intersection crashes by logistic regression. Traffic Inj Prev. 2012;13(3):300–307. doi: 10.1080/15389588.2011.653841.

[50] Zhang K, Hassan M. Crash severity analysis of nighttime and daytime highway work zone crashes. PLoS One. 2019;14(8):e0221128. doi: 10.1371/journal.pone.0221128.

[51] Elliott MA. Predicting motorcyclists' intentions to speed: effects of selected cognitions from the theory of planned behaviour, self-identity and social identity. Accid Anal Prev. 2010;42(2):718–725. doi: 10.1016/j.aap.2009.10.021.

[52] Tunnicliff DJ, Watson BC, White KM, et al. Understanding the factors influencing safe and unsafe motorcycle rider intentions. Accid Anal Prev. 2012;49:133–141. doi: 10.1016/j.aap.2011.03.012.

[53] Mannering FL, Grodsky LL. Statistical analysis of motorcyclists' perceived crash risk. Accid Anal Prev. 1995;27(1):21–31. doi: 10.1016/0001-4575(94)00041-J.

[54] Cordellieri P, Sdoia S, Ferlazzo F, et al. Driving attitudes, behaviours, risk perception and risk concern among young student car-drivers, motorcyclists and pedestrians in various EU countries. Transp Res Part F Traffic Psychol Behav. 2019;65:56–67. doi: 10.1016/j.trf.2019.07.012.

[55] Girotto E, de Andrade SM, González AD, et al. Professional experience and traffic accidents/near-miss accidents among truck drivers. Accid Anal Prev. 2016;95(Pt A):299–304. doi: 10.1016/j.aap.2016.07.004.

[56] Rosenbloom T. Job burnout, effort-reward imbalance and time pressure as predictors of safety among military truck drivers. J Transp Health. 2022;24:101248. doi: 10.1016/j.jth.2021.101248.

[57] Castro M, Paleti R, Bhat CR. A spatial generalized ordered response model to examine highway crash injury severity. Accid Anal Prev. 2013;52:188–203. doi: 10.1016/j.aap.2012.12.009.

[58] Kwayu KM, Kwigizile V, Lee K, et al. Discovering latent themes in traffic fatal crash narratives using text mining analytics and network topology. Accid Anal Prev. 2021;150:105899. doi: 10.1016/j.aap.2020.105899.

[59] Kockelman KM, Kweon Y-J. Driver injury severity: an application of ordered probit models. Accid Anal Prev. 2002;34(3):313–321. doi: 10.1016/S0001-4575(01)00028-8.

[60] Rusli R, Haque MM, Saifuzzaman M, et al. Crash severity along rural mountainous highways in Malaysia: an application of a combined decision tree and logistic regression model. Traffic Inj Prev. 2018;19(7):741–748. doi: 10.1080/15389588.2018.1482537.

[61] Xie K, Ozbay K, Yang H. Secondary collisions and injury severity: a joint analysis using structural equation models. Traffic Inj Prev. 2017;19(2):189–194. doi: 10.1080/15389588.2017.1369530.

[62] Gariazzo C, Bruzzone S, Finardi S, et al. Association between extreme ambient temperatures and general indistinct and work-related road crashes. A nationwide study in Italy. Accid Anal Prev. 2021;155:106110. doi: 10.1016/j.aap.2021.106110.

[63] Lee J, Chae J, Yoon T, et al. Traffic accident severity analysis with rain-related factors using structural equation modeling – a case study of Seoul city. Accid Anal Prev. 2018;112:1–10. doi: 10.1016/j.aap.2017.12.013.

[64] Behnood A, Mannering F. The temporal stability of factors affecting driver-injury severities in single-vehicle crashes: some empirical evidence. Anal Methods Accid Res. 2015;8:7–32. doi: 10.1016/j.amar.2015.08.001.

[65] Strathman JG, Wachana P, Callas S. Analysis of bus collision and non-collision incidents using transit its and other archived operations data. J Safety Res. 2010;41(2):137–144. doi: 10.1016/j.jsr.2010.02.003.

[66] Anowar S, Yasmin S, Tay R. Comparison of crashes during public holidays and regular weekends. Accid Anal Prev. 2013;51:93–97. doi: 10.1016/j.aap.2012.10.021.

[67] Regan, M.A., Young, K., Lee, J. (Eds.), 2009. Driver distraction: theory, effects, and mitigation. New York: CRC Press.

[68] Haque MM, Ohlhauser AD, Washington S, et al. Decisions and actions of distracted drivers at the onset of yellow lights. Accid Anal Prev. 2016;96:290–299. doi: 10.1016/j.aap.2015.03.042.

[69] Yuan R, Abdel-Aty M, Gu XIN, et al. A unified modeling framework for lane change intention recognition and vehicle status prediction. Physica A. 2023;632:129332 10.1016/j.physa.2023.129332