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Research Article

Modeling Injury Severity for Nighttime and Daytime Crashes by Using Random Parameter Logit Models Accounting for Heterogeneity in Means and Variances

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Understanding the factors contributing to crash severity, along with their influence degrees across different times of day, can assist in better highway design and in developing effective countermeasures for ameliorating highway safety (especially during nighttime). This study examines the influences of risk factors on crash severity, based on comparisons of nighttime and daytime crashes. By using a random parameter approach to account for unobserved heterogeneity, multivariate logit (RPML) models are proposed to analyze the crash severity based on the explanatory factors in terms of the crash, traffic, speed, road geometry, and sight characteristics. The goodness-of-fit and predictive measures highlight the better performance of the proposed models relative to standard models, as the proposed models reduce the unobserved heterogeneity and yield higher precision. In addition, the elasticity effects of the factors are calculated to investigate and compare their impact degrees in daytime and nighttime crashes. The findings could potentially be utilized to guide highway design and policies and to develop specific safety countermeasures.

1. Introduction

In 2015, the World Health Organization reported 217711 deaths in traffic crashes in China, with a death rate per 100000 vehicles 1.7 times that in the US [1]. According to the Traffic Management Bureau of the Public Security Ministry [2] in China, highway crashes account for only 5% of all roadway crashes, but the fatalities involved in highway crashes account for almost 10% of all fatalities. Moreover, approximately one-third of the very severe roadway crashes in 2015 (involving 10 or more fatalities) occurred on highways. To mitigate the damage caused by highway crashes and ensure efficient safety countermeasures in China, a wide range of research efforts have been devoted to reducing the occurrence of crashes and the severity of their outcomes [3–5].

Nighttime crashes are a serious problem for the safe operation of highways, owing to the reduction in visibility [6]. According to the National Highway Traffic Safety Administration (NHTSA), the nighttime traffic death rate (deaths per 100 million vehicle miles) is 4.4 times higher than that of the day [6]. In 2017, approximately 47% of fatal crashes in the US occurred during the night [7]. In April 2018, 36% of all fatalities in the EU member states occurred during the night. Moreover, this percentage increased to greater than 50% between November and January, owing to the longer nights during winter [8]. Driving during the nighttime with poor visibility increases the frequency and severity of crashes on highways [9]. Despite the substantially smaller traffic volumes, the crash frequency increases at night [6]. Several crash databases and reports have shown that the crash severity during nighttime is over two times higher than that in the daytime [10, 11]. In particular, the average number of fatalities per 100 nighttime crashes in Italy is 3.5, compared to 1.7 during the daytime [12]. These findings underscore the requirement for and importance of research efforts on the time-of-day variation effects of contributing factors. For example, drivers have less time to compensate for the reduced sight distance in the nighttime, leading to more frequent crashes and more severe outcomes. Several previous pieces of evidence illustrated significant variations in the influences of factors affecting injury severities during different periods of the day in the large truck crashes (morning vs. afternoon) [13] and multivehicle crashes (daytime vs. nighttime) [14]. Overall, more efforts should be undertaken to investigate the differences in the effects of the contributing factors influencing daytime and nighttime crashes, with possible different generation mechanisms.

Sight distance is an essential element for identifying risks and ensuring safe driving. Drivers at night can monitor and detect the road environment and driving behaviors of the surrounding vehicles ahead with illuminating headlights at an average distance of 50 m [15]. Driving at night may be riskier because of the shorter available sight distance. As a basis of highways, roadway alignments have significant impacts on highway safety. In particular, horizontal curves greatly aggravate safety issues because the sight distances of most drivers at night vary from those during daytime [16]. In the evening, drivers may be unable to accurately identify the curvature to correct the direction and speed of their vehicles [17] but may be capable of accomplishing effective operations during the daytime. Considering the horizontal alignment during night driving, it is critical to consider a nighttime impact difference evaluation from both policy and engineering perspectives.

Identifying the significant factors and impact levels thereof affecting the injury severity for daytime and nighttime crashes is critical for policymakers and roadway engineers in China. This study intends to use the findings of past research as a basis for understanding the potential influence mechanisms of variables (i.e., stopping sight distance) on the crash severity.

We are particularly interested in the following questions.

(1) What are the contributing determinants to crash severity on highways? What differences exist between daytime and nighttime crashes?

(2) To what extent do the key variables affect the crash severity, respectively?

(3) Do any differences exist in the influence trends and degrees of the significant variables? Do these factors show time-of-day variations?

This study lays a foundation for a total evaluation of crash injury outcomes during certain time-of-day periods, e.g., by presenting the magnitude of the problem and providing guidance for future research.

1.1. Related Work. In previous traffic safety studies, many statistical models have been developed for examining the attributes affecting crash consequences. A comprehensive literature review of the modeling methodologies for crash severity is presented as follows. In addition, related studies on the time-of-day variations and temporal instabilities are discussed.

1.2. Related Work of Modeling Methodology for Crash Frequency. Based on crash datasets, the statistical analyses in previous studies on crash data have typically addressed the resulting injury severity of crashes. The application of count data involves determining the number of crashes occurring over segments of a specified length. Various multivariate count models have been developed for jointly analyzing crash frequencies with different degrees of injury, including negative binomial models [18], Poisson model [19], Bayesian models [20, 21], and so on.

1.3. Related Work of Modeling Methodology for Crash Severity. A growing body of research efforts (Table 1) has analyzed the crash severity based on the multinomial logit model, ordered probit model, Markov-switching model, Bayesian random parameters models, grouped random parameters models, correlated random parameters models, latent class models, random parameter multinomial logit models (mixed logit models), and other models, and a wide range of factors have been found to potentially influence the injury severities.

As given in Table 1, among all of the contributing factors, a wide range of roadway, traffic, and environmental characteristics influence both the likelihood and injury severity of crashes [37]. By accommodating heterogeneity in the means and variances, the random parameter's approaches can provide much more flexibility in tracking the unobserved heterogeneity and indicate the statistical superiority in terms of accuracy [35, 36, 38, 39], which is utilized in this study.

1.4. Related Works of Time-of-Day Variation and Temporal Instability. The time-of-day variation and temporal stability of the factors affecting crash severity have become innovation issues and major concerns. Wei et al. [40] suggested a significant time-of-day effect in truck crashes, as crashes occurring in the afternoons and at night were more severe. Evans et al. [41] found that drivers perform worse regarding perceptions of risk and difficulty in the nighttime. Das and Abdel-Aty [42] found that the average daily traffic significantly influenced urban rear-end crash occurrences. Jung et al. [43] revealed that rainfall conditions lead to higher injury severity levels in crashes. Ackaah et al. [44] found that nighttime traffic crashes resulted in more severe injury outcomes and that most collisions occurred in the early hours of the night. Musunuru et al. [45] verified the hypothesis that horizontal curves with higher proportions of traffic at night experience more crashes. Malyshkina et al. [26] indicated that the crash frequency changes between states over time by adopting a Markov-switching model. Malyshkina and Mannering [26] and Xiong et al. [27] also found that crash severity is unstable over short periods, along with unobserved heterogeneity. Behnood and Mannering [13] analyzed the time-of-day variations and temporal instability of factors affecting injury severity in large truck crashes over eight years. Moreover, the present research suggests that certain factors among roadway geometrics, pavement, weather, and traffic characteristics show temporal instability over time-of-day or year periods [38, 46–51].

However, the previous studies have mainly separately examined crash frequency or crash severity, such that several potential risk factors might be ignored owing to their insignificance in single modeling work. Additional efforts should be devoted to investigating both the frequency of crashes and their resulting severity and to revealing the remarkable differences and similarities in the significant factors and their influences. This study intends to identify the crash contributors causing more frequent crashes and more serious injuries by separating daytime and nighttime crashes. The findings of this study could be utilized to determine the implementation of specific safety countermeasures aimed at daytime and nighttime crashes. A comprehensive understanding of the above issues can be obtained by establishing explicit relationships between the crash frequency and severity and the characteristics of drivers, vehicles, roadway alignments, traffic, and weather conditions.

2. Methodology

2.1. Random Parameter Logit Approach. To analyze the significant factors resulting in the crash injury severity, we propose random parameter multivariate logit (RPML) models with heterogeneity in means and variances and define the injury severity function as

$$T_{sk} = \beta_s X_{sk} + \varepsilon_{sk}, \tag{1}$$

where T_{sk} denotes the injury severity function determining the probability of crash severity s in crash k, X_{sk} is a vector of explanatory variables (roadway, traffic, and environment characteristics variables), β_s is the estimate parameters for category s, and ε_{sk} is a stochastic error term assumed to follow the generalized extreme value distribution [52].

With the assumption of the extreme value distributed ε_{sk}, a standard multinomial logit model is proposed to allow for parameter variances varying across observations, specified as [53]

$$P_{sk} = \int \frac{e^{\beta_k X_{sk}}}{\sum e^{\beta_k X_{sk}}} f(\beta|\varphi)\mathrm{d}\beta, \tag{2}$$

where $f(\beta|\varphi)$ denotes the probability density function of the random vector β, and φ is a vector of parameters of the probability density function (mean and variance).

According to Seraneeprakarn et al. [35], heterogeneity in the mean and variance is specified as

$$\beta_s = \beta + \delta_s M_s + \sigma_s e^{\omega_s D_s} \nu_s, \tag{3}$$

where M_s, D_s denote the vectors capturing heterogeneity in means for crash severity s and standard deviation σ_s with corresponding parameter vector ω_s, respectively, and ν_s is a disturbance term.

The attributes relating to the roadway, traffic, and environment characteristics of heterogeneity are contained in M_s, D_s. If the random parameter logit model shows significance in the vector of M_s, D_s, the model characterizes the unobserved heterogeneity in means and variances. If the model shows only significance in the vector M_s, the model only characterizes heterogeneity in means.

2.2. Elasticity Effect on Crash Severity. Elasticity effects in random parameter multivariate logit (RPML) models are also calculated to measure the magnitude of the impact of specific variables on the probability of crash severity s in crash k.

$$E_{x_{sl}}^{P_{sk}} = \frac{\partial P_{sk}}{\partial x_{sl}} \times \frac{x_{sl}}{P_{sk}}, \tag{4}$$

where P_{sk} denotes the probability of crash severity s in crash k and x_{sl} is the value of variable l of crash severity s.

2.3. Model Estimation. Model estimation like log-likelihood function (LL) is conducted in this study. The log-likelihood function is

$$LL = \sum_{n=1}^{N} \left(\sum_{m=1}^{M} \sigma_{mn} \left[\beta_m X_{mn} - LN \sum_{\forall M} e^{\beta_M X_{Mn}} \right] \right), \tag{5}$$

where X_{mn}, σ_{mn} denote the vector and standard deviation of explanatory variables (roadway, traffic, and environment characteristics variables), respectively, and β_m is the estimated parameter.

Bayesian information criterion (BIC) is also used for model comparison, which is a generalized version of the Akaike information criterion (AIC) considering the Bayesian equivalent.

$$\begin{aligned} BIC &= n_P \ln(n) - 2\ln(LL), \\ AIC &= 2k - 2\ln(LL), \end{aligned} \tag{6}$$

where n_P, LL denote the number of model parameters and the likelihood function, respectively.

Then, the log-likelihood ratio was used to examine the model goodness-of-fitness.

$$R^2 = \frac{LL(\beta)}{LL(0)}, \tag{7}$$

where $LL(\beta)$, $LL(0)$ denote the log-likelihood at the convergence of the "full model" and "constant model only," respectively.

2.4. Data Description. We used three-year (2015–2017) crash data from Beijing-Shanghai highway, as collected by the traffic management department. Beijing-Shanghai highway (G2) from Xinyi to Jiangdu in Jiangsu Province is a region of rolling terrains with a total length of 259.5 km and a design speed of 120 km/h. The average annual daily traffic volume (AADT) ranges from 31158 to 68836, and the proportion of cars and trucks is 59.0% and 12.9%, respectively. The data contained a total of 3159 crashes, including data on the vehicle type, time, location, climate, road surface condition, and casualty condition. Among the datasets, rear-end crashes, scrub crashes, and other types of crashes were included. In addition, roadway geometric features were collected from road design and construction drawings, including those concerning horizontal alignment, vertical alignment, and interchanges. In addition, the definitions of daytime and nighttime crashes were extracted from the detailed descriptions in the dataset.

We divided the road into 426 different sections according to the horizontal alignment, vertical alignment, and interchange [18]. We obtained the average annual daily traffic (AADT) of 426 sections as reported by roadway management agencies.

We adopted the crash severity levels from the Ministry of Public Security in China [54] as follows:

(1) Light crash: a crash causing minor injuries to one to two persons or causing property damage less than 1000 CNY (approximately $154.19 USD)

(2) Minor crash: a crash causing serious injuries to one to two persons, minor injuries to more than two, or property damage of more than 1000 CNY but less than 30000 CNY

(3) Severe crash: a crash causing one to two deaths, serious injuries to three to ten persons, or property damage of more than 30000 CNY but less than 60000 CNY

(4) Very severe crash: a crash causing more than two deaths, serious injuries to more than 10 persons, or property damage of more than 60000 CNY. No very severe crashes were identified in this dataset. Both the crash frequency and outcomes regarding the three severity levels (light injury, minor injury, and severe injury) were calibrated and analyzed based on multivariate models.

Table 2 provides the crash statistics for different injury severities during daytime and nighttime, including both two-vehicle and multivehicle crashes. Additionally, all casualties and property losses involved in a two-vehicle or multivehicle crash were considered to evaluate the injury severity outcomes.

The operating speeds of cars and trucks were calculated by segments according to different geometric features, based on the models in Specifications for Highway Safety Audit [54] published in 2016 (Appendix A).

In general, the stopping sight distance is the shortest distance required for an ordinary driver to react and to slow down or stop when encountering obstacles while driving at a certain speed. Based on the Guidelines for Design of Highway Grade-Separated Intersections [55], the stopping sight distances of cars and trucks were calculated based on (8) and (9), respectively.

$$S_{\text{car}} = \frac{v_{85}t}{3.6} + \frac{(v_{85}/3.6)^2}{2gf}. \tag{8}$$

Truck drivers can see the vertical planes of obstacles at a considerable distance from their perspective at a low speed, but it is also difficult to control the vehicle owing to the poor braking performance. Despite the high viewpoint, truck drivers also lose sight in places with limited lateral line-of-sight vision.

$$S_{\text{truck}} = \frac{v_{85}t}{3.6} + \frac{(v_{85}/3.6)^2}{2g(f+i)}. \tag{9}$$

In the above equations, S_{car}, S_{truck} denote the stopping sight distance of the car and truck, respectively, v_{85} is the operating speed (km/h), t is the reaction time, set as 2.5 s generally (judging time as 1.5 s, running time as 1.0 s), g is the gravitational acceleration, i.e., 9.8 m/s^2, i is the longitudinal grade, and f is the longitudinal friction coefficient between the truck tires and road surface and generally takes a value of 0.17.

Corrugated beam guardrails are commonly set in the middle and beside a road across all sections, and the inside (outside) guardrails along the left-turn (right-turn) horizontal curves will affect the drivers' sight. We consider the largest transverse clear distance for confirming sight safety, i.e., the distance between the curve of sight and the track. When the plane curve is sharp, the transverse clear distance should be determined on the inside lane. We calculated the required stopping sight distance of each section for safety as follows:

$$H = R_s\left(1 - \cos\frac{\gamma}{2}\right), \tag{10}$$

where H denotes the largest transverse clear distance, R_s is the radius of the inside lane, and γ is the central angle of the line of sight.

The crash, traffic, speed, geometric, and sight characteristics of the independent variables are given in Table 3.

3. Results

3.1. Model Specification and Overall Measure of Fit for Crash Severity

3.1.1. Model Specification and Overall Measure of Fit. Concerning the crash severity, we take a detailed discussion of the contributing determinants during different periods based on random parameter logit approaches. As given in Table 4, both the AIC and BIC values of the approaches indicate the superiority of the random parameter logit model with heterogeneity in the means and variances. In addition, R^2 of the random parameter logit model with heterogeneity in the means and variances is 0.23, indicating that the model is more appropriate than the other two models.

Accordingly, this model is adopted to research the crash severity, and the results for all crashes, daytime crashes, and nighttime crashes are given in Tables 5–7. The elasticity effects of all significant variables are given in Tables 5–7.

3.1.2. Model Estimation Result or Crash Severity. Model results of the random parameter logit model with heterogeneity in means and variance for all crashes, for daytime crashes, and for nighttime crashes are given in Tables 5–7.

Table 1: Summary of approaches in the analysis of crash severity.

Methodological approach	Significant variables	Previous research
Multinomial logit model	Time of day; driver gender; usage of alcohol/drugs; seat belt usage; horizontal curve; weather condition; number of vehicles involved	Harb et al. [22]; Chen et al. [23]
Ordered probit model	Driver gender; driver age; fatigue driving; peak time; sharp curve; vertical grade; weather condition; icy pavement; speed; crash type; light condition	Chen and Chen [24]; Ghasemzadeh and Ahmed [25]
Markov switching model	Driver gender; driver age; usage of alcohol; AADT; fatigue driving; weekday; weather condition; visibility distance; lane number; speed limit	Malyshkina and Mannering [26]; Xiong et al. [27]
Bayesian random parameters models	Daily vehicle miles traveled; segments length; number of populations; median annual household income	Huang et al. [28]
Grouped random parameters models	Freeway; arterial; collector; AADT; median barrier; intersection; population; number of tracks/lanes; road/train speed	Cai et al. [29]; Heydari et al. [30]
Correlated random parameters models	Interstate; local road; speed limit; number of lanes; road geometry; road location; lighting condition; road surface; weather condition; time of day; time of year	Ahmed et al. [31]
Multilevel models	Ratio of older drivers; region; driver behavior; alcohol use; speeding; vehicle age; nighttime; nonclear weather	Park et al. [32]; Park et al. [33]
Latent class models	Cyclist/pedestrian counts; AADT; lane use; number of schools/ subway stations; number of lanes; speed limit; arterial/ramp	Heydari et al. [34]
Random parameters logit model with heterogeneity in means and variances	Occupant/driver age; fatigue driving; physical impairment; speeding; collision angle; lane number; weather condition; wet road surface	Seraneeprakarn et al. [35]; Kim et al. [36]

Table 2: Descriptive statistics of crash frequency.

Code	Variables name	Day		Night		Total
		Frequency	Percentage (%)	Frequency	Percentage (%)	
1	Light injury	2083	65.94	869	27.52	2952
2	Minor injury	124	3.93	57	1.80	181
3	Severe injury	17	0.53	9	0.28	26
Total		2224	70.40	935	29.60	3159

3.2. Discussion for Crash Severity

3.2.1. Crash Characteristics. Regarding the crash characteristics, the pavement indicator has significantly positive effects on the minor injury outcomes of all crashes and daytime crashes, but a negative effect on the nighttime crashes. Overall, icy pavement tends to increase the light injury likelihood and decrease the severe injury likelihood for all the periods. This counterintuitive finding might be explained by the risk-compensation psychology of drivers being more cautious and conservative when faced with icy surfaces [56].

The positive elasticity effects in Table 7 reveal that the season is significant for nighttime crashes only, suggesting higher probabilities of light and severe injury crashes in autumn or winter (light injury: 0.0019; severe injury: 0.0008). This finding is consistent with the research of Wang et al. [57], in which the authors argued that the low temperature during winter could potentially lead to slippery surface conditions with the effects of snow and ice.

3.2.2. Traffic Characteristics. As noted for the traffic characteristics, AADT shows significance in the daytime and for all crashes. The elasticity effects in Table 5 for all crashes indicate that a greater traffic volume increases the possibility of light injury crashes and decreases the probability of minor and severe injury crashes (light injury: 0.0227; minor injury: −0.0062; severe injury: −0.0165). A high traffic volume may lead to congestion or poor operation conditions, whereas higher travel speeds are associated with low traffic volumes [9, 58]. This finding is consistent with that of Zeng et al. [4], who noted that a vehicle traveling at high speed with low traffic volumes will significantly increase the severity level of any crash involving it.

3.2.3. Speed Characteristics. Regarding the speed characteristics, the value of $\Delta V_{O\text{-truck}}$ is found to significantly affect the severity level in all three models, with higher possibility of severe injury outcomes. This result is expected because of the poor brake performance of trucks at high speeds, which imposes greater hazards due to the stronger crash tendency of trucks [59].

However, $\Delta V_{O\text{-car}}$ shows significance for all crashes and daytime crashes. Positive values indicate higher probabilities of light and minor injury crashes with a greater speed difference between cars.

Table 3: Descriptive statistics of key variables.

Variables names	Definition	Min.	Max.	Mean	SD
Crash characteristics					
Weather	1, rainy or snowy day (6.1%); 0, otherwise (93.9%)	0	1	0.06	0.2
Pavement condition	1, ice pavement (2.1%); 0, otherwise (97.9%)	0	1	0.02	0.1
Season	1, occurred from February to April; 2, occurred from May to July; 3, occurred from August to October; 4, occurred in November, December, or January.	1	4	2.5	1.4
Traffic characteristics					
Interchange	1, occurred near an interchange (25.8%); 0, otherwise (74.2%)	0	1	0.1	0.3
Bridge	1, occurred on bridge (12.4%); 0, otherwise (87.6%)	0	1	0.3	0.5
AADT	Average annual daily traffic volume	31158	68836	52850.9	10581.5
Speed characteristics					
$V_{O-\text{car}}$ (km/h)	Operating speed of cars	95.1	193.8	119.6	21.5
$\Delta V_{O-\text{car}}$ (km/h)	Speed difference of cars with adjacent segment	−78.0	85.9	−0.2	34.9
$V_{O-\text{truck}}$ (km/h)	Operating speed of trucks	61.3	104.8	79.3	12.1
$\Delta V_{O-\text{truck}}$ (km/h)	Speed difference of trucks with adjacent segment	−25.7	34.0	−1.4	21.3
ΔV_O (km/h)	Speed difference between cars and trucks	12.6	104.7	40.3	16.0
Geometric characteristics					
R_{front} (m)	Radius of the plane curve of front section	5597	1000000	429300.6	490879.2
L_{front} (m)	Length of the plane curve of front section	450	3267	1224.2	711.3
R_{present} (m)	Radius of the horizontal curve (plane curve of present section)	5597	1000000	380669.6	481087.0
L_{present} (m)	Length of the horizontal curve (plane curve of present section)	680	3676	1638.4	639.0
R_{back} (m)	Radius of the plane curve of back section	5597	1000000	438578.3	492254.3
L_{back} (m)	Length of the plane curve of back section	450	3676	1233.8	759.3
$i_{\min}$ (%)	Minimum longitudinal grade of current section	−1.6	1.6	0.0	0.4
$Ls_{\min}$ (m)	Length of the longitudinal slope corresponding to the minimum grade	240.0	1740.0	773.3	296.0
$i_{\max}$ (%)	Maximum longitudinal grade of current section	-2.50	2.50	0.00	0.97
$Ls_{\max}$ (m)	Length of the longitudinal slope corresponding to the maximum grade	362.0	1740.0	652.6	248.0
Sight characteristics					
S_{car} (m)	Stopping sight distance of cars	244.0	1004.8	423.6	139.6
S_{truck} (m)	Stopping sight distance of trucks	52.0	279.4	82.7	24.3
H_{car} (m)	Horizontal clearance of cars	0.02	6.5	1.4	1.5
H_{truck} (m)	Horizontal clearance of trucks	0	0.2	0.05	0.04

Car denotes vehicles with a wheelbase less than 7 m and power greater than 15 kW/t, and truck denotes vehicles with a wheelbase more than 7 m or powerless than 15 kW/t [54].

Table 4: Goodness-of-fit measure of random parameter logit approaches for all-time.

Model	Log-likelihood	AIC	BIC	R^2
Random parameter logit model only	−277.31	670.63	1018.87	0.16
With heterogeneity in means	−263.45	652.18	994.58	0.19
With heterogeneity in means and variances	−256.24	641.84	947.48	0.23

3.2.4. Geometric Characteristics. Concerning geometric characteristics, L_{back} and $Ls_{\max}$ show significance affecting the injury severity of the three types of crashes. R_{front} and L_{present} only show the significance of daytime crashes. The positive estimated parameter of R_{front} (-1.96×10^{-3}) indicates a decreased possibility of severe injury crashes with a greater R_{front} during daytime. This finding was as expected for greater R_{front} could provide greater stopping sight distance (SSD) [54], which suggests a low risk of severe outcomes in previous research evidence [58]. The negative elasticity effects show that a greater L_{present} results in decreased probabilities of minor injury and severe injury crash during the daytime. This result is as expected because the drivers can operate more smoothly when adapted to the curvature of the sections, enabling them to take proper reactions in time to potential hazards.

3.2.5. Elasticity Effects. To evaluate the differences in the effects of significant variables across different periods, the elasticity effects were also determined for each injury severity level. As shown in Figures 1(a)–1(d), the elasticity effects of the pavement, $\Delta V_{O-\text{truck}}$, L_{back}, and $Ls_{\max}$, indicate different influences on crash severity across the different times of day.

An evident decrease in injury severity is observed relating to the pavement indicator, as the icy pavement may result in increased light injury and decreased severe injury

Table 5: Model results of the random parameter logit model with heterogeneity in means and variance for all crashes.

Variables	Parameter estimate	t-stat	Elasticity effect Light injury	Minor injury	Severe injury
[MI] constant	−3.65	−3.37			
Crash characteristics					
[MI] pavement	1.25	2.65	0.0015	0.0011	−0.0026
Traffic characteristics					
[SI] AADT	-5.25×10^{-5}	-2.81	0.0227	−0.0062	−0.0165
Speed characteristics					
[SI] $\Delta V_{O-\text{car}}$	−0.024	−3.23	5.83×10^{-5}	2.51×10^{-5}	-8.34×10^{-5}
[SI] $\Delta V_{O-\text{truck}}$	0.048	2.59	-5.42×10^{-5}	-3.13×10^{-5}	8.55×10^{-5}
Geometric characteristics					
[LI] L_{back}	2.91×10^{-4}	2.31	1.87×10^{-3}	-2.33×10^{-3}	0.46×10^{-3}
[LI] $Ls_{\max}$	3.06×10^{-3}	2.19	1.06×10^{-3}	0.68×10^{-3}	-1.74×10^{-3}
Random parameters					
[MI] constant	−4.65	−4.17			
Standard deviation	4.63	3.97			
Heterogeneity in the means of random parameter					
[MI] constant L_{present}	-3.42×10^{-3}	−4.51			
Heterogeneity in the variances of random parameter					
[MI] constant $\Delta V_{O-\text{car}}$	0.068	4.41			
Number of observations	3159				
Number of estimated parameters	60				
Log-likelihood	−256.24				
AIC	641.84				
BIC	947.48				
R^2	0.23				

Table 6: Model results of the random parameter logit model with heterogeneity in means and variance for daytime crashes.

Variables	Parameter estimate	t-stat	Elasticity effect Light injury	Minor injury	Severe injury
[MI] constant	−2.21	−2.88			
Crash characteristics					
[MI] pavement	1.66	2.42	0.0017	0.0008	−0.0025
Traffic characteristics					
[Li] *AADT*	-5.71×10^{-5}	−3.22	0.0193	−0.0045	−0.0148
Speed characteristics					
[SI] $\Delta V_{O-\text{car}}$	−0.033	−2.43	4.85×10^{-5}	3.36×10^{-5}	8.21×10^{-5}
[SI] $\Delta V_{O-\text{truck}}$	0.049	4.52	0.41×10^{-5}	-3.77×10^{-5}	3.36×10^{-5}
Geometric characteristics					
[Mi] R_{front}	1.01×10^{-6}	2.87	-1.26×10^{-3}	3.23×10^{-3}	-1.96×10^{-3}
[Mi] L_{present}	-6.60×10^{-3}	−2.51	2.93×10^{-3}	-2.35×10^{-3}	-0.58×10^{-3}
[Mi] L_{back}	-7.35×10^{-4}	−3.12	-0.96×10^{-3}	-0.69×10^{-3}	1.65×10^{-3}
[SI] $Ls_{\max}$	-4.05×10^{-3}	−2.64	1.32×10^{-3}	0.34×10^{-3}	-1.66×10^{-3}
Random parameters					
[LI] constant	−3.35	−7.43			
Standard deviation	2.73	4.36			
Heterogeneity in the means of random parameter					
[MI] constant AADT	-6.78×10^{-6}	−7.84			
[SI] constant L_{present}	-1.12×10^{-3}	−3.97			
Heterogeneity in the variances of random parameter					
[MI] constant $\Delta V_{O-\text{car}}$	0.097	3.82			
Number of observations	2224				
Number of estimated parameters	26				
Log-likelihood	−136.17				
AIC	388.34				
BIC	703.73				
R^2	0.25				

Table 7: Model results of the random parameter logit model with heterogeneity in means and variance for nighttime crashes.

Variables	Parameter estimate	t-stat	Elasticity effect		
			Light injury	Minor injury	Severe injury
Crash characteristics					
[MI] season	−0.56	−2.91	0.0019	−0.0027	0.0008
[MI] pavement	−2.11	−2.58	0.0009	−0.0004	−0.0005
Speed characteristics					
[SI] $V_{O\text{-truck}}$	0.037	3.21	-6.48×10^{-5}	-0.16×10^{-5}	6.64×10^{-5}
Geometric characteristics					
[Mi] L_{back}	8.86×10^{-4}	4.63	-1.19×10^{-3}	1.72×10^{-3}	-0.53×10^{-3}
[Mi] $Ls_{\max}$	3.00×10^{-3}	2.27	1.47×10^{-3}	0.34×10^{-3}	-1.81×10^{-3}
Random parameters					
[MI] constant	−9.26	−4.30			
Standard deviation	3.68	3.15			
Heterogeneity in the means of random parameter					
[LI] constant L_{present}	8.19×10^{-3}	4.67			
[MI] constant L_{present}	-5.16×10^{-3}	−3.51			
Heterogeneity in the variances of random parameter					
[LI] constant L_{back}	-3.86×10^{-4}	−2.38			
Number of observations	935				
Number of estimated parameters	24				
Log-likelihood	−100.13				
AIC	316.27				
BIC	615.87				
R^2	0.26				

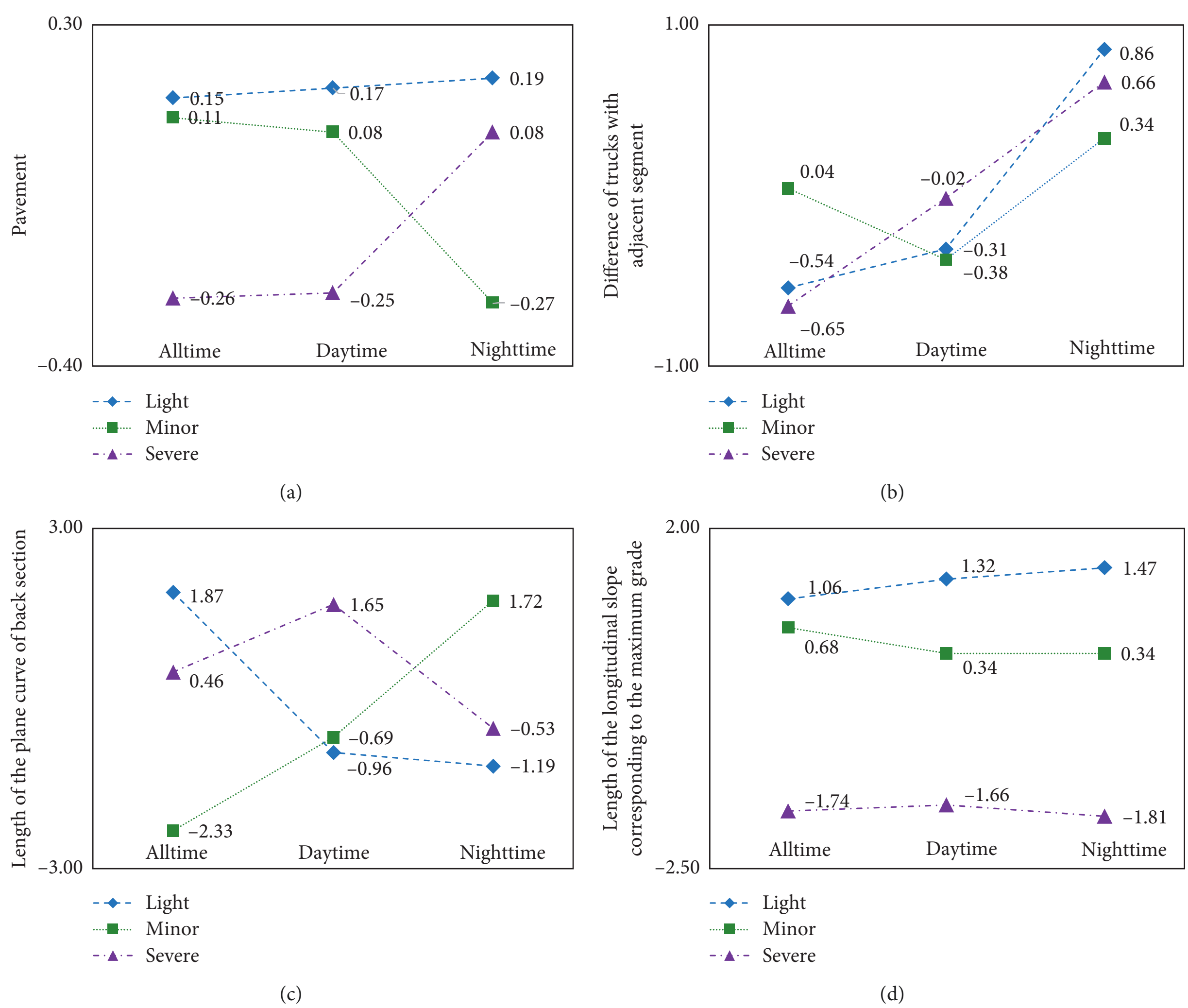

Figure 1: 95% confidence interval of the elasticity effects of contributing factors on crash severity. (a) Pavement (10^{-2}), (b) speed difference of trucks with adjacent segment ($\Delta V_{O\text{-truck}}$) ($10^{-5}$), (c) length of the plane curve of back section (L_{back}) (10^{-3}), and (d) length of the longitudinal slope corresponding to the maximum grade ($LS_{\max}$) (10^{-3}).

Table 8: Operating speed prediction model for plane curve section.

Connection type	Vehicle type	Prediction model
Entrance: SC	Car	$v_{\text{middle}} = -24.212 + 0.834v_{\text{in}} + 5.729 \ln R_{\text{now}}$
	Truck	$v_{\text{middle}} = -9.432 + 0.963v_{\text{in}} + 1.522 \ln R_{\text{now}}$
Entrance: CC	Car	$v_{\text{middle}} = 1.277 + 0.942v_{\text{in}} + 6.19 \ln R_{\text{now}} - 5.959 \ln R_{\text{back}}$
	Truck	$v_{\text{middle}} = -24.472 + 0.990v_{\text{in}} + 3.629 \ln R_{\text{now}}$
Exist: CS	Car	$v_{out} = 11.946 + 0.908v_{\text{middle}}$
	Truck	$v_{\text{out}} = 5.217 + 0.926v_{\text{middle}}$
Exist: CC	Car	$v_{\text{out}} = -11.299 + 0.936v_{\text{middle}} - 2.060 \ln R_{\text{now}} + 5.203 \ln R_{\text{front}}$
	Truck	$v_{\text{out}} = 5.899 + 0.925v_{\text{middle}} - 1.005 \ln R_{\text{now}} + 0.329 \ln R_{\text{front}}$

v_{in}, v_{middle}, and v_{out} denote the operating speed at the entrance, midpoint, and exist of the plane curve, respectively (km/h) and R_{back}, R_{now}, and R_{front} denote the radius of the plane curve of the back, present, and back section, respectively (m).

Table 9: Operating speed conversion model for longitudinal slope section.

Longitudinal slope		Adjustment values of operating speed	
		Car	Truck
Upslope	3% ≤ slope ≤ 4%	Decline by 5 km/h every 1000 m	Decline by 10 km/h every 1000 m
	Slope > 4%	Decline by 8 km/h every 1000 m	Decline by 20 km/h every 1000 m
Downslope	3% ≤ slope ≤ 4%	Increase by 10 km/h every 500 m	Increase by 7.5 km/h every 500 m
	Slope > 4%	Increase by 20 km/h every 500 m	Increase by 15 km/h every 500 m

Table 10: Operating speed conversion model for curved slope section.

Connection type	Vehicle type	Prediction model
Entrance: SC	Car	$v_{\text{middle}} = -31.67 + 0.547v_{\text{in}} + 11.71 \ln R_{\text{now}} - 0.176I_{\text{now1}}$
	Truck	$v_{\text{middle}} = 1.782 + 0.859v_{\text{in}} + 1.196 \ln R_{\text{now}} - 0.51I_{\text{now1}}$
Entrance: CC	Car	$v_{\text{middle}} = 0.75 + 0.802v_{\text{in}} + 2.717 \ln R_{\text{now}} - 0.281I_{\text{now1}}$
	Truck	$v_{\text{middle}} = 1.798 + 0.977v_{\text{in}} + 0.248 \ln R_{\text{now}} - 0.133I_{\text{now1}} + 0.23 \ln R_{\text{back}}$
Exist: CS	Car	$v_{\text{out}} = 27.294 + 0.72v_{\text{middle}} - 1.444I_{\text{now2}}$
	Truck	$v_{\text{out}} = 13.49 + 0.797v_{\text{middle}} - 0.6971I_{\text{now2}}$
Exist: CC	Car	$v_{\text{out}} = 1.819 + 0.839v_{\text{middle}} + 1.427 \ln R_{\text{now}} + 0.782 \ln R_{\text{front}} - 0.48I_{\text{now2}}$
	Truck	$v_{\text{out}} = 26.837 + 0.83v_{\text{middle}} - 3.039 \ln R_{\text{now}} + 0.109 \ln R_{\text{front}} - 0.594I_{\text{now2}}$

v_{in}, v_{middle}, and v_{out} denote the operating speed at the entrance, midpoint, and exist of the plane curve, respectively (km/h), R_{back}, R_{now}, and R_{front} denote the radius of the plane curve of back, present, and back section, respectively (m), and I_{now1}, I_{now2} denote the different slopes at the front and back ends of the curve (%).

outcomes. This finding is in line with Fountas et al. [60] who argued that under poor weather conditions, crashes are more likely to result in slight injuries. Moreover, drivers tend to drive slowly and cautiously when faced with slippery pavement surfaces [61], and they may compensate for the high crash risk by exhibiting greater driving caution [56]. In addition, the effects of pavement show different impact trends on minor injury crashes during daytime and nighttime (0.0008 and −0.0004, respectively).

Regarding the speed characteristics, it is observed that a higher $\Delta V_{O-\text{truck}}$ tends to consistently result in an increased probability of severe injury outcomes, but the elasticity effect in nighttime is approximately twice that in daytime crashes (6.64×10^{-5} to 3.36×10^{-5}). A similar phenomenon was reported by Fors and Lundkvist [11], and a comprehensive comparison of the substantial differences indicates a higher risk level for trucks with greater speed differences at night. This finding is as expected, as drivers have more time to perceive and react properly to hazards and prevent crashes [4], as they have better vision in the daytime [9].

The negative signs for the elasticity effects of L_{back} indicate that light crashes are less likely to occur in segments with greater L_{back} values during daytime and nighttime. However, the greater L_{back} decreases and increases the probability of minor and severe crashes in the daytime, respectively. Interestingly, the nighttime crashes show the opposite trend. This finding may be attributed to the fact that the greater length of the back section allows for careless and fatigue driving, with higher speeds in the daytime. In addition, the dark conditions during nighttime might encourage drivers to exercise greater driving caution as a type of compensation for the shorter vision [60].

As for $Ls_{\max}$, the elasticity effects show a consistent impact tendency during daytime and nighttime, with little variation in the degree of influence. Specifically, the probabilities of minor crashes and severe crashes increase and decrease by 0.034% (0.034%) and 0.166% (0.181%) during daytime (nighttime), respectively, with a 1% increase in Ls_{max}. This finding can be counterintuitive, as a steeper grade limits the driver's vision with less time for the driver to react to potential hazards [9, 62]. However, the maximum grade of segments on this highway is no more than 2.5%, and they are mainly located in bridge segments; accordingly, the results may be attributed to the lower posted speed limits on bridges [4].

4. Conclusion and Future Direction

Using crash data from the Beijing-Shanghai highways collected by the traffic management department (2015–2017), this study examined the effects of the contributing factors on the crash injury severity on highways for all, daytime, and nighttime crashes. With three possible crash injury severity outcomes (light injury, minor injury, and severe injury), a wide range of explanatory factors including the crash type, traffic, speed, geometric, and sight characteristics affecting the crash frequency and severity were considered.

The random parameter logit model with heterogeneity in means and variance is adopted, owing to the best good-of-fit with lower AIC and BIC values and higher R^2 (641.84, 947.48, and 0.23, respectively). Based on the proposed models, several explanatory variables are found to produce different effects in terms of their influences on the crash frequency and resulting injury severity. The estimated results reveal that several variables produce temporally different effects in their impacts with different injury severity outcomes, indicating injury severity transferability across the time of day.

The findings of the results for crash severity underscore the importance of accounting for the time variation effects of significant variables on the crash frequency and the resulting injury severity outcomes on highways. The findings of this study should be of particular value for roadway designers and traffic management departments in promoting highway safety targeted at daytime and nighttime crashes, respectively. For example, during evening, active light-emitting warning messages, speed limit signs, and other reasonable measures should be set up to prevent drivers from speeding or fatigue; education programs or other measures should be implemented to ensure the safe driving of professional drivers. It is also important for traffic management agencies to strengthen the enforcement against risky driving behaviors; the lane distribution measures for different vehicle types should be suggested to reduce the interference between cars and trucks; and during the design stage, the alignments of curve-grade sections should be optimized to provide continuous and coordinated roadway three-dimensional conditions.

Notably, this study is not free of limitations, such as the small percentage of severe injury crashes in the dataset (26 total, accounting for 0.85%). Future research can benefit from crash data across a wider range of years and/or considering the sociodemographic characteristics of drivers, owing to the high contribution of driving behaviors to roadway crashes [47]. Then, advanced statistical models accounting for the unobserved heterogeneity can be adopted to provide more accurate results [63, 64].

Appendix

A. The Operating Speed Prediction Models

The operating speed prediction models are shown in Specifications for Highway Safety Audit [54] for the plane curve section, longitudinal slope section, and curved slope section. The connection of the plane curve is classified as three types: straight line to curved section (SC), curved section to curved section (CC), and curved section to straight line (CS). As for the vehicle type, car denotes vehicles with a wheelbase less than 7 m and power greater than 15 kW/t, and truck denotes vehicles with a wheelbase more than 7 m or powerless than 15 kW/t [54] (Table 8).

A.1. The operating speed prediction model for plane curve section

A.2. The operating speed conversion model for the longitudinal slope section is given in Table 9

A.3. The operating speed prediction model for curved slope section is given in Table 10

Data Availability

The data used to support the findings of this study have not been made available because the crash dataset is obtained through the traffic police department and the administrative department. The data cannot be disclosed due to confidentiality requirements.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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