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*Research Article*

# Do Expressway Interchanges Increase Crash Injury Severities? Insights Using Temporal Instability and Unobserved Heterogeneity

**Fang Wang,[1] Chenzhu Wang ,[2] Said M. Easa,[3] Siqi Lian,[4] Fei Chen ,[2] and Jianchuan Cheng[2]**

[1]*School of Civil Engineering and Hydraulic Engineering, Ningxia University, 539 West Helanshan Road, Yinchuan, Ningxia 750021, China*
[2]*School of Transportation, Southeast University, 2 Sipailou, Nanjing, Jiangsu 210096, China*
[3]*Department of Civil Engineering, Toronto Metropolitan University, Toronto, ON, Canada*
[4]*Department of Civil and Environmental Engineering, University of Michigan, 2350 Hayward Street, Ann Arbor, MI 48109, USA*

Correspondence should be addressed to Chenzhu Wang; 448617592@qq.com

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Expressway crashes in interchange areas are a critical concern in China, posing significant economic and social challenges. Utilizing three years of crash data from the Beijing–Shanghai Expressway, this study investigates the transferability and heterogeneity of crash characteristics between interchange and noninterchange areas, as well as the temporal shifts in factors influencing injury severity levels. The research employs four series of random parameters logit models to estimate three potential crash injury severity outcomes of severe injury, minor injury, and no injury (based on the most severely injured individual in each crash) and to identify key determinants, encompassing driver, vehicle, roadway, environmental, temporal, traffic, and crash attributes. Likelihood ratio tests and out-of-sample predictions are utilized to assess the temporal stability and transferability of crash area characteristics. Additionally, the marginal effects of various determinants are calculated to understand their influence across different year periods and crash types. Key variables such as overspeed, single-vehicle, AADT (annual average daily traffic volume), $Ls_{min}$, and other crash type indicators are identified as significant random parameters, demonstrating heterogeneity in means and variances. Notable distinctions are observed between interchange and noninterchange crashes, indicating nontransferability, with most significant indicators revealing temporal instabilities. Furthermore, factors such as multivehicle involvement, buses, and nighttime conditions are identified as risk indicators, notably increasing the likelihood of severe injuries. These insights are invaluable for expressway designers and decision-makers, aiding in understanding the contributing mechanisms of various elements. This study suggests that stricter enforcement measures are crucial to prevent random lane changes, particularly at interchange entrances and exits. Additionally, effective management strategies and enforcement countermeasures should be implemented to mitigate crash injury outcomes in both interchange and noninterchange areas.

## 1. Introduction

In China, 211,074 motor vehicle crashes occurred in 2020, causing 55,950 fatalities, 214,442 injuries, and property losses of 1228.0 million CNYs [1]. In recent years, the traffic fatalities caused by expressway crashes accounted for nearly 10% of the total traffic fatalities [2], posing enormous economic and social threats. Due to the complexities of infrastructure, traffic, and driving environment, the interchange areas are the bottleneck segments of safety and efficiency in expressways. Hu et al. [3] stated that the crashes that occurred in interchange areas expressways made up 34.5% of all expressway crashes, while the proportion of lengths of interchange areas was only 9.5% from 2014 to 2016 in Jiangsu province. Therefore, it is vital to analyze the injury levels of interchange areas and adopt effective strategies to eliminate the risk levels. However, few studies addressed the injury severity outcomes of crashes that occurred in interchange areas on China expressways.

Recent studies indicated that the determinants affecting injury severity outcomes include driver, vehicle, roadway, environmental, temporal, and crash characteristics. Due to the discrete form of crash data, many discrete-data models were chosen to analyze traffic crashes, among which the logit approach is widely used [4]. However, the traditional probit/logit model assumes that the effects of multiple elements on injury levels are fixed in different crash observations, which is inconsistent with the natural situation. Moreover, traffic crashes are complicated interactions among multiple factors in various crash observations; one specific factor might influence the injury outcomes of various crashes differently. Otherwise, not all the data determining the injury outcomes could be collected, while the missing data or biased information might lead to unobserved heterogeneities [5]. To overcome the biased estimation results and errors of model structure caused by such issues, the random parameters logit models that allow the parameters to vary across observations have been shown to have better performance and utilized in many research efforts [6–17]. Nowadays, the random parameters logit approaches have been proven to demonstrate statistical superiority and accuracy and capture more flexibility in estimating the unobserved heterogeneity by considering heterogeneity in the means and variances [18–22]. For instance, while analyzing the gender differences in injury severities of nonhelmeted motorcyclists, Wang et al. [21] validated that the random parameters logit model with heterogeneity in the means and variances outperformed other models based on $\chi^2$ tests. Moreover, Hou et al. [23] also indicated the advantages of this model in predictive performance.

Other than capturing the unobserved heterogeneities, temporal instability over year, season, or time of day might be another critical issue [24]. The potential explanation might be the changes in perception, decision, and reaction of drivers in hazardous situations along with the safety attitudes. (During the driving process, the driver's decision-making behavior can be regarded as a continuous trade-off between the brain's autonomic response and the controlled process. The driver's autonomic response is instinctive. For example, when an object or vehicle suddenly appears in front of the vehicle, the driver tends to make an instinctive autonomic response. The driver's controlled process is the behavior made after thinking for a certain period of time. For example, when he percepts the road ahead in advance, the driver could make an appropriate judgment on braking, lane change, and other behaviors. Both the autonomic response and the controlled process will change with the accumulation of driving experience and the changes in road environments. Therefore, there are different potential factors affecting the driver's behavior in different time periods, and even when faced with the stimulation of the same factors, the corresponding behavior of the driver will change over time, ultimately resulting in determinants that affect the injury severity of highway crash and the instability of their effects on time), which mainly suffer from variations in various elements including interactions between vehicles, roadway alignment, environment, the influence of macroeconomics, and so on [24]. A growing body of research efforts has confirmed that the effects of the determinant variables change by the year [11, 16, 25–29]. For instance, Dabbour et al. [30] established a year-separate model to analyze the effects of driver and vehicle characteristics on the driver injury levels of rear-end crashes in North Carolina from 2004 to 2015. Then, the year-separate model was compared with the aggregated model based on the overall sample. The estimation results show that the accuracy of the aggregated model was less than that of the year-specific model. This might be explained by a structural variation, indicating that the influence of the determinants affecting injury severity will change over the year.

Therefore, this paper intends to reveal the transferability and temporal variation of the significant factors affecting injury severities in interchange crashes (IAC) and non-interchange crashes (NIAC). The transferability of the IA and NIA crashes could make sense for better understanding the time-varying effects of determinants on expressway safety planning, management, and policy in interchange areas in China expressways. Capturing the unobserved heterogeneity, the random parameters logit models with heterogeneity in means and variances are used to reveal the injury severities based on Beijing-Shanghai Expressway crash data in 2017–2019.

Figure 1 presents the research flowchart. First, the two heterogeneity models and collected data are described, followed by the likelihood ratio tests and out-of-sample predictions. Then, the estimation results and corresponding specific recommendations are discussed. Finally, the summaries and conclusions are presented. These findings have significant implications for roadway designers and traffic management to implement appropriate and effective measurements to eliminate the risk levels of IAC and NIAC.

This study aims at (i) investigating the variations in factors determining injury severities in IAC and NIAC crashes; (ii) offering an explicit understanding of how determinants about injury severities in IAC and NIAC vary over different year periods; (iii) distinguishing and interpreting the unobserved heterogonous effects. Not only could the findings of this paper fill the knowledge gaps in the temporal instability and the determinants' transferability among IAC and NIAC but they also serve as references for roadway designers seeking to mitigate crash occurrences and severities in interchange areas.

## 2. Data Collection

The crash dataset occurred in the Beijing–Shanghai Expressway being a 4-lane national expressway was collected from the traffic management department, which is designed according to the highway standard with level to rolling terrains. The cross-section width is 28.0 m, and the design speed is 120 km/h. A total of 4,238 traffic crashes were collected from 2017 to 2019. As the number of fatalities is few, the fatal and incapacitating injuries are merged into one classification: severe injury. Then, the injury severity was

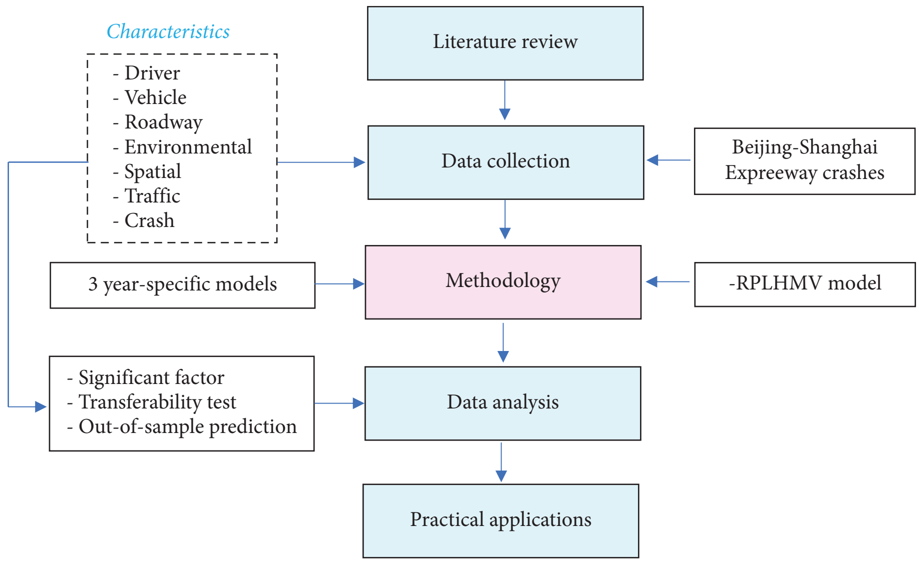


Figure 1: Outline of study activities.

classified into three levels: severe injury (fatal/incapacitating injury), minor injury (incapacitating/possible injury), and no injury (property damage only) [29]. Specifically, the term "fatal injury" includes not only fatalities that occur at the scene of the accident but also those resulting from crashes within 30 days of being injured. Additionally, the term "possible injury" refers to cases where there was no visible trauma, but individuals reported experiencing pain and potential injuries as a result of the crashes. The statistical results of the severity of crashes in interchange areas and noninterchange areas over the years are shown in Table 1, and Figure 2 shows the injury severity distribution. Table 2 presents the descriptive statistics of significant variables in IAC and NIAC from 2017 to 2019 in terms of the driver, vehicle, roadway, environmental, temporal, traffic, and crash characteristics.

## 3. Methodology

*3.1. Random Parameter Logit Approaches.* Capturing heterogeneity in means and variances, the random parameters logit approaches are utilized in this paper to analyze the determinants affecting the injury severity levels of IAC and NIAC. First, the propensity function could be expressed as follows [5]:

$$S_{ij} = \beta_i \mathbf{X}_{ij} + \varepsilon_{ij}, \qquad (1)$$

where $S_{ij}$ represents the function determining the probability of injury severity outcome $i$ in crash $j$, $\mathbf{X}_{ij}$ is a vector of explanatory variables, $\beta_i$ denotes the estimated parameter, and $\varepsilon_{ij}$ is a stochastic error term assumed to follow the generalized extreme-value distribution.

A standard multinomial logit model is defined when $\varepsilon_{ij}$ follows an assumption of extreme-value distribution [31]:

$$P_{ij} = \int \frac{e^{\beta_i \mathbf{X}_{ij}}}{\sum e^{\beta_i \mathbf{X}_{ij}}} f(\beta \mid \varphi) \mathrm{d}\beta, \qquad (2)$$

Table 1: Crash observations for IAC and NIAC across 2017–2019.

| Year | Classification | No injury | Minor injury | Severe injury | Total |
|---|---|---|---|---|---|
| 2017 | IAC | 150 | 51 | 23 | 224 |
| | NIAC | 1029 | 331 | 39 | 1399 |
| 2018 | IAC | 149 | 48 | 12 | 209 |
| | NIAC | 1218 | 399 | 58 | 1675 |
| 2019 | IAC | 154 | 37 | 6 | 197 |
| | NIAC | 1164 | 315 | 21 | 1500 |
| 2017–2019 | IAC | 453 | 136 | 41 | 630 |
| | NIAC | 3411 | 1045 | 118 | 4574 |

where $f(\beta \mid \varphi)$ represents the probability density function of the random vector $\beta$ and $\varphi$ denotes the mean or variance vector of the parameters of the probability density function.

While capturing the heterogeneity in the mean and variance, $\beta_{ij}$ is defined as a vector of estimable parameters [20]:

$$\beta_{ij} = \beta_i + \delta_{ij}\mathbf{M}_{ij} + \sigma_{ij} e^{\omega_{ij}\mathbf{D}_{ij}} \nu_{ij}, \qquad (3)$$

where $\mathbf{M}_{ij}$ and $\mathbf{D}_{ij}$ represent the vectors capturing heterogeneity in the mean and standard deviation $\sigma_{ij}$ with the corresponding parameter vector $\omega_{ij}$ for injury severity $i$ in crash $j$, respectively. $\delta_{ij}$ is associated with the estimated parameters, while $\nu_{ij}$ is a disturbance term. The $\mathbf{M}_{ij}$ and $\mathbf{D}_{ij}$ characterize the heterogeneity caused by attributes. (If the random parameters logit model shows significance in the vector of $\mathbf{M}_{ij}$ and $\mathbf{D}_{ij}$, the model characterizes the unobserved heterogeneity in means and variances. If the model shows only significance in the vector $\mathbf{M}_{ij}$, the model only characterizes heterogeneity in means).

The Halton sampling method is adopted to optimize efficiency and prediction performance [31]. Other than uniform, lognormal, or triangular distribution, the normal distribution is adopted in this study, which could provide a better statistical fit for random parameters logit modeling

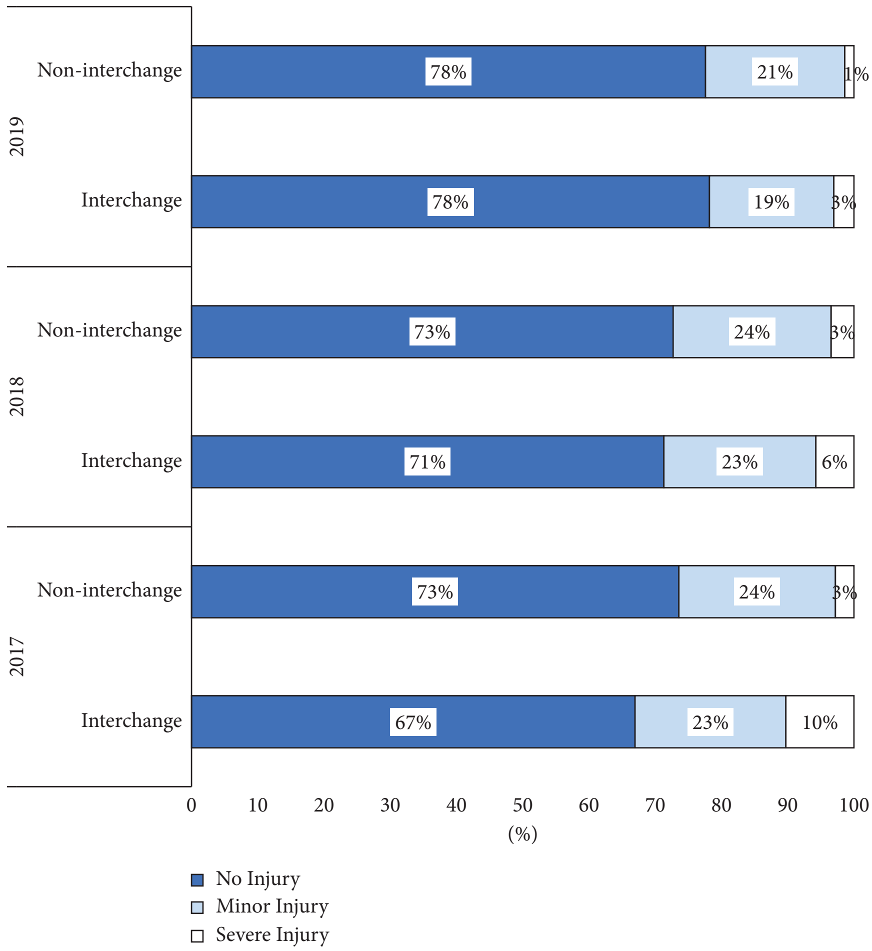


Figure 2: Injury severity for interchange and noninterchange crashes from 2017 to 2019.

approaches [32]. After simulating different Halton draws, 500 Halton draws are used based on the maximum likelihood approach considering the trade-off among performance accuracy and estimation efficiency [33].

*3.2. Likelihood Ratio Test.* To examine the temporal shifts of determinants affecting the injury outcomes of IAC or NIAC across different years, along with the transferability among IAC and NIAC, three series of likelihood ratio tests (LRTs) are estimated. The first two series are used for temporal instability tests, and the third one is the transferability tests. According to the research of Behnood and Mannering [34], there are two kinds of LRTs concerning the temporal instability. The first is the pairwise test, which could propose to determine whether there are significant differences between each year's model. Another is the global test, which is used to consider all years as a whole and determine if there are significant differences overall. Moreover, the third LRT being the transferability tests is conducted to identify overall group differences, with the group classified by the interchange area and noninterchange area crashes.

Specifically, the first pairwise test is used to compare models in two different periods and explore whether the parameter estimation is stable from one time period to another:

$$\chi^2_{t_1} = -2\left[\mathrm{LL}\left(\beta_{t_2 t_1}\right) - \mathrm{LL}\left(\beta_{t_1}\right)\right], \tag{4}$$

where $\mathrm{LL}(\beta_{t_2 t_1})$ is the log-likelihood (LL) value of the model containing the convergence parameter of $t_2$ using the crash data in $t_1$ and $\mathrm{LL}(\beta_{t_1})$ is the log-likelihood value of the model using $t_1$ data and convergence parameters. To obtain two test results for each model comparison, the $t_1$ and $t_2$ subgroups could be reversed in this test, where the degree of freedom of the model is equal to the number of estimated parameters in the $\mathrm{LL}(\beta_{t_2 t_1})$ model. The LRT results of interchange and noninterchange crashes are, respectively, shown in Tables 3 and 4.

The second LRT being the global test is also used to explore whether the model parameters in two-year periods remain temporally stable, expressed as follows:

$$\chi^2_{t_2} = -2\left[\mathrm{LL}\left(\beta_{2017-2019,g}\right) - \sum_{2017}^{2019} \mathrm{LL}\left(\beta_{t,g}\right)\right], \tag{5}$$

Table 2: Descriptive statistics (standard deviation in parentheses) of significant variables in IAC and NIAC across 2017 to 2019.

| Variable | 2017 | | 2018 | | 2019 | |
|---|---|---|---|---|---|---|
| | IAC | NIAC | IAC | NIAC | IAC | NIAC |
| *Driver characteristics* | | | | | | |
| Safety (1 if speeding, 0 otherwise) | 0.820 (0.379) | 0.734 (0.442) | 0.880 (0.325) | 0.690 (0.462) | 0.481 (0.500) | 0.422 (0.494) |
| Safety (1 if improper action, 0 otherwise) | 0.126 (0.241) | 0.238 (0.426) | 0.120 (0.325) | 0.305 (0.461) | 0.516 (0.500) | 0.577 (0.494) |
| *Vehicle characteristics* | | | | | | |
| Vehicle indicator (1 if the number of vehicles involved in the crash is 1, 0 otherwise) | 0.503 (0.499) | 0.619 (0.486) | 0.389 (0.488) | 0.470 (0.499) | 0.222 (0.415) | 0.453 (0.498) |
| Vehicle indicator (1 if the number of vehicles involved in the crash is 2, 0 otherwise) | 0.425 (0.496) | 0.328 (0.470) | 0.526 (0.500) | 0.448 (0.497) | 0.655 (0.476) | 0.466 (0.499) |
| Vehicle indicator (1 if the number of vehicles involved in the crash is > 2, 0 otherwise) | 0.072 (0.315) | 0.053 (0.224) | 0.086 (0.280) | 0.082 (0.274) | 0.123 (0.329) | 0.082 (0.274) |
| Vehicle type (1 if passenger car, 0 otherwise) | 0.353 (0.522) | 0.326 (0.516) | 0.350 (0.478) | 0.384 (0.509) | 0.326 (0.454) | 0.365 (0.514) |
| Vehicle type (1 if minibus, 0 otherwise) | 0.372 (0.582) | 0.380 (0.596) | 0.411 (0.670) | 0.504 (0.565) | 0.444 (0.506) | 0.352 (0.350) |
| Vehicle type (1 if bus, 0 otherwise) | 0.123 (0.325) | 0.009 (0.096) | 0.057 (0.232) | 0.029 (0.169) | 0.003 (0.056) | 0.016 (0.125) |
| Vehicle type (1 if van, 0 otherwise) | 0.037 (0.168) | 0.002 (0.041) | 0.017 (0.130) | 0.013 (0.113) | 0.009 (0.097) | 0.006 (0.074) |
| Vehicle type (1 if truck, 0 otherwise) | 0.125 (0.241) | 0.051 (0.221) | 0.137 (0.344) | 0.182 (0.386) | 0.481 (0.500) | 0.471 (0.499) |
| Vehicle type (1 if heavy truck, 0 otherwise) | 0.090 (0.189) | 0.047 (0.212) | 0.360 (0.480) | 0.256 (0.436) | 0.009 (0.097) | 0.025 (0.156) |
| *Roadway characteristics* | | | | | | |
| $R_{\text{front}}$: radius of the plane curve of front section ($10^3$ m) | 227.067 (442.562) | 457.565 (494.325) | 220.402 (316.263) | 481.521 (495.938) | 280.408 (443.770) | 424.397 (490.117) |
| $R_{\text{present}}$: radius of the horizontal curve ($10^3$ m) | 476.616 (497.219) | 326.923 (464.013) | 517.533 (496.929) | 332.438 (466.003) | 431.369 (491.346) | 389.388 (483.171) |
| $R_{\text{back}}$: radius of the plane curve of back section ($10^3$ m) | 286.600 (476.896) | 464.218 (494.944) | 334.140 (417.280) | 470.771 (495.394) | 353.047 (418.818) | 343.797 (425.888) |
| $L_{\text{front}}$: length of the plane curve of front section ($10^3$ m) | 0.943 (0.734) | 1.248 (0.711) | 0.770 (0.469) | 1.276 (0.727) | 1.394 (0.756) | 1.448 (0.705) |
| $L_{\text{present}}$: length of the horizontal curve ($10^3$ m) | 1.356 (0.589) | 1.631 (0.657) | 1.312 (0.551) | 1.671 (0.608) | 1.291 (0.689) | 1.449 (0.759) |
| $L_{\text{back}}$: length of the plane curve of back section ($10^3$ m) | 0.906 (0.622) | 1.269 (0.757) | 0.801 (0.486) | 1.257 (0.747) | 1.234 (0.712) | 1.449 (0.759) |
| $i_{\min}$: minimum longitudinal grade of current section (%) | 0.011 (0.486) | 0.107 (3.219) | 0.039 (0.557) | 0.018 (0.432) | 0.014 (0.428) | 0.021 (0.415) |
| $\text{Ls}_{\min}$: length of the longitudinal slope corresponding to the minimum grade (m) | 675.024 (274.427) | 750.991 (274.959) | 669.874 (250.212) | 747.066 (277.276) | 711.898 (322.849) | 354.359 (396.518) |
| $i_{\max}$: maximum longitudinal grade of current section (%) | 0.034 (1.215) | 0.103 (1.422) | 0.072 (1.206) | 0.062 (1.100) | 0.075 (1.034) | 0.078 (1.205) |
| $\text{Ls}_{\max}$: length of the longitudinal slope corresponding to the maximum grade (m) | 644.096 (244.602) | 619.512 (237.251) | 648.509 (146.288) | 605.182 (225.170) | 481.942 (156.365) | 523.322 (40.203) |
| *Environmental characteristics* | | | | | | |
| Weather (1 if fine, 0 otherwise) | 0.324 (0.375) | 0.329 (0.381) | 0.193 (0.338) | 0.124 (0.330) | 0.272 (0.445) | 0.273 (0.445) |
| Weather (1 if cloudy, 0 otherwise) | 0.383 (0.399) | 0.337 (0.425) | 0.331 (0.471) | 0.379 (0.485) | 0.658 (0.475) | 0.585 (0.493) |
| Weather (1 if rainy, 0 otherwise) | 0.174 (0.458) | 0.250 (0.409) | 0.326 (0.469) | 0.361 (0.480) | 0.051 (0.219) | 0.085 (0.279) |
| Weather (1 if foggy, 0 otherwise) | 0.054 (0.299) | 0.023 (0.149) | 0.097 (0.296) | 0.042 (0.201) | 0.009 (0.097) | 0.026 (0.159) |
| Weather (1 if snowy, 0 otherwise) | 0.054 (0.156) | 0.061 (0.239) | 0.051 (0.221) | 0.068 (0.252) | 0.016 (0.125) | 0.036 (0.187) |
| Road surface condition (1 if icy, 0 otherwise) | 0.012 (0.111) | 0.019 (0.138) | 0.017 (0.130) | 0.034 (0.181) | 0.015 (0.180) | 0.016 (0.131) |
| *Temporal characteristics* | | | | | | |
| Monday (1: occurs on Monday, otherwise 0) | 0.138 (0.368) | 0.113 (0.317) | 0.080 (0.272) | 0.116 (0.320) | 0.098 (0.298) | 0.122 (0.327) |
| Tuesday (1: occurs on Tuesday, otherwise 0) | 0.126 (0.330) | 0.118 (0.323) | 0.103 (0.304) | 0.110 (0.313) | 0.146 (0.353) | 0.136 (0.343) |

Table 2: Continued.

| Variable | 2017 | | 2018 | | 2019 | |
|---|---|---|---|---|---|---|
| | IAC | NIAC | IAC | NIAC | IAC | NIAC |
| Wednesday (1: occurs on Wednesday, otherwise 0) | 0.162 (0.379) | 0.138 (0.345) | 0.183 (0.387) | 0.129 (0.335) | 0.130 (0.336) | 0.119 (0.324) |
| Thursday (1: occurs on Thursday, otherwise 0) | 0.198 (0.330) | 0.167 (0.373) | 0.183 (0.387) | 0.180 (0.384) | 0.161 (0.368) | 0.137 (0.344) |
| Friday (1: occurs on Friday, otherwise 0) | 0.120 (0.343) | 0.155 (0.362) | 0.149 (0.356) | 0.172 (0.377) | 0.165 (0.371) | 0.171 (0.376) |
| Saturday (1: occurs on Saturday, otherwise 0) | 0.144 (0.330) | 0.178 (0.382) | 0.131 (0.338) | 0.156 (0.363) | 0.171 (0.377) | 0.186 (0.390) |
| Sunday (1: occurs on Sunday, otherwise 0) | 0.114 (0.368) | 0.131 (0.337) | 0.171 (0.377) | 0.138 (0.345) | 0.130 (0.336) | 0.129 (0.335) |
| Early morning (1: occurs from 00 : 00 to 05 : 59, otherwise 0) | 0.467 (0.498) | 0.485 (0.500) | 0.211 (0.409) | 0.247 (0.431) | 0.310 (0.463) | 0.276 (0.447) |
| Morning (1: occurs from 6 : 00 to 11 : 59, otherwise 0) | 0.198 (0.389) | 0.180 (0.384) | 0.349 (0.477) | 0.278 (0.448) | 0.212 (0.409) | 0.248 (0.432) |
| Afternoon (1: occurs from 12 : 00 to 17 : 59, otherwise 0) | 0.198 (0.399) | 0.216 (0.411) | 0.246 (0.431) | 0.290 (0.454) | 0.288 (0.453) | 0.295 (0.456) |
| Evening (1: occurs from 18 : 00 to 23 : 59, otherwise 0) | 0.138 (0.379) | 0.120 (0.325) | 0.194 (0.396) | 0.185 (0.389) | 0.190 (0.392) | 0.182 (0.386) |
| Spring (1: occurs in spring, otherwise, 0) | 0.246 (0.262) | 0.266 (0.442) | 0.440 (0.497) | 0.346 (0.476) | 0.320 (0.365) | 0.207 (0.405) |
| Summer (1: occurs in summer, otherwise, 0) | 0.246 (0.472) | 0.219 (0.414) | 0.234 (0.424) | 0.213 (0.410) | 0.263 (0.244) | 0.284 (0.348) |
| Autumn (1: occurs in autumn, otherwise, 0) | 0.281 (0.468) | 0.277 (0.448) | 0.200 (0.400) | 0.254 (0.435) | 0.279 (0.270) | 0.305 (0.317) |
| Winter (1: occurs in winter, otherwise, 0) | 0.228 (0.446) | 0.237 (0.425) | 0.126 (0.332) | 0.188 (0.390) | 0.138 (0.191) | 0.204 (0.315) |
| *Traffic characteristics* | | | | | | |
| Bridge (1: the section occurring is the bridge section, otherwise 0) | 0.305 (0.439) | 0.287 (0.452) | 0.269 (0.444) | 0.278 (0.448) | 0.244 (0.430) | 0.267 (0.443) |
| AADT: Average annual daily traffic volume | 45634.6 (9917.2) | 52156.030 (11215.396) | 45110.6 (9096.3) | 53365.1 (10855.6) | 50261.0 (11469.3) | 52496.4 (10851.5) |
| *Crash characteristics* | | | | | | |
| Sideswipe (1: the crash type is sideswipe, otherwise 0) | 0.006 (0.111) | 0.004 (0.065) | 0.011 (0.106) | 0.020 (0.140) | 0.013 (0.112) | 0.014 (0.117) |
| Run-off-road (1: the crash type is run-off-road, otherwise 0) | 0.036 (0.111) | 0.056 (0.231) | 0.057 (0.232) | 0.055 (0.229) | 0.028 (0.166) | 0.063 (0.243) |
| Overturned (1: the crash type is overturned, otherwise 0) | 0.012 (0.156) | 0.002 (0.041) | 0.000 (0.000) | 0.002 (0.046) | 0.000 (0.000) | 0.000 (0.000) |
| Hit fixed object (1: the crash type is hit fixed object, otherwise 0) | 0.275 (0.299) | 0.281 (0.449) | 0.269 (0.444) | 0.324 (0.468) | 0.255 (0.362) | 0.311 (0.463) |
| Rear-end (1: the crash type is rear-end, otherwise 0) | 0.401 (0.477) | 0.264 (0.441) | 0.362 (0.461) | 0.304 (0.492) | 0.350 (0.433) | 0.493 (0.500) |
| Other crash types (1: other crash types, otherwise 0) | 0.269 (0.500) | 0.393 (0.488) | 0.301 (0.452) | 0.298 (0.490) | 0.360 (0.438) | 0.125 (0.331) |
| Crash indicator (1 if flat-tire, 0 otherwise) | 0.006 (0.111) | 0.006 (0.077) | 0.000 (0.000) | 0.000 (0.000) | 0.003 (0.056) | 0.001 (0.030) |
| Crash indicator (1 if mechanical fault, 0 otherwise) | 0.000 (0.000) | 0.002 (0.041) | 0.000 (0.000) | 0.002 (0.046) | 0.000 (0.000) | 0.000 (0.000) |
| EMS shorter than 20 minutes (1: rescue response time is shorter than 20 minutes, otherwise 0) | 0.048 (0.189) | 0.055 (0.228) | 0.034 (0.182) | 0.038 (0.191) | 0.006 (0.079) | 0.020 (0.141) |
| EMS among 20–60 minutes (1: rescue response time is 20–60 minutes, otherwise 0) | 0.557 (0.501) | 0.564 (0.496) | 0.600 (0.490) | 0.544 (0.498) | 0.152 (0.359) | 0.264 (0.441) |
| EMS greater than 60 minutes (1: rescue response time greater than 60 minutes, otherwise 0) | 0.395 (0.500) | 0.381 (0.486) | 0.366 (0.482) | 0.418 (0.493) | 0.842 (0.365) | 0.715 (0.451) |

Table 3: Likelihood ratio test results of crash in IAC in different years.

| $t_2$ | $t_1$ 2017 | 2018 | 2019 |
|---|---|---|---|
| 2017 | — | 32.18 (10) [>99.21%] | 48.26 (6) [>99.99%] |
| 2018 | 42.75 (6) [>99.99%] | — | 39.52 (6) [>99.99%] |
| 2019 | 52.61 (6) [>99.99%] | 36.94 (10) [>99.42%] | — |

*Note.* () is the degree of freedom of the model; [] is the confidence level.

Table 4: Likelihood ratio test results of NIAC in different years.

| $t_2$ | $t_1$ 2017 | 2018 | 2019 |
|---|---|---|---|
| 2017 | — | 72.68 (22) [>99.99%] | 96.26 (15) [>99.99%] |
| 2018 | 94.25 (20) [>99.99%] | — | 85.19 (15) [>99.99%] |
| 2019 | 79.62 (20) [>99.99%] | 109.22 (22) [>99.99%] | — |

*Note.* () is the degree of freedom of the model; [] is the confidence level.

where $\mathrm{LL}(\beta_{2017-2019,g})$ is the LL value of the convergence model for the aggregated data of crash classification $g$ (IAC and NIAC) in the use period of 2017–2019 and $\mathrm{LL}(\beta_{t,g})$ is the log-likelihood value of the model using the crash data and convergence parameter of year $t$ for crash classification $g$. The degree of freedom in this test statistic is equal to the number of statistically significant parameters in the separate model minus the number of statistically significant parameters in the combined model [4].

The third series of LRT was used to judge the transferability among IAC and NIAC [14], and the corresponding test statistics are expressed as follows:

$$\chi_g^2 = -2\left[\mathrm{LL}\left(\beta_{\mathrm{joint},t}\right) - \mathrm{LL}\left(\beta_{\mathrm{Interchange},t}\right) - \mathrm{LL}\left(\beta_{\mathrm{Non-interchange},t}\right)\right], \tag{6}$$

where $\mathrm{LL}(\beta_{\mathrm{joint},t})$ is the log-likelihood value of the convergence model combining IAC and NIAC data when period $t$ is used and $\mathrm{LL}(\beta_{\mathrm{Interchange},t})$ and $\mathrm{LL}(\beta_{\mathrm{Non-interchange},t})$ are log-likelihood values of convergence models for IAC and NIAC at year $t$, respectively.

*3.3. Out-of-Sample Prediction.* In addition to the standard LRT [4], out-of-sample prediction (OOSP) is another effective method adopted in many studies to analyze the temporal instability and the nontransferability between crash types [21, 25, 28, 35, 36].

According to recent studies [23, 25], OOSP is calculated by adopting one model's estimated parameters to predict another model's observed crashes and explore the nontransferability among different crash models. There are two types of OOSP. The first could be used to predict the injury severity levels in another year by using IAC or NIAC in one year to reveal the temporal shifts. Another OOSP is estimated by proposing the estimated parameters of the IAC model to predict the NIAC data and reveal the difference in its prediction results. Corresponding to the estimation model, 500 Halton samples are also taken for OOSP. OOSP can be carried out by calculating the mean probability difference, and the simulation approach implemented to compute the predicted probabilities is specific as follows [21, 23]:

$$P_j(i) = \frac{1}{N}\sum_{\mathbf{n}=1}^{\mathbf{N}} \frac{\mathbf{e}^{\left[\left(\beta_{\mathrm{i}}+\delta_{\mathrm{ij}}\mathbf{M}_{\mathrm{ij}}+\sigma_{\mathrm{ij}}e^{\omega_{\mathrm{ij}}\mathbf{D}_{\mathrm{ij}}}\nu_{\mathrm{ij}}\right)\mathbf{X}_{\mathbf{ij}}\right]}}{\sum_{\mathbf{i}=1}^{\mathbf{I}}\mathbf{e}^{\left[\left(\beta_{\mathrm{i}}+\delta_{\mathrm{ij}}\mathbf{M}_{\mathrm{ij}}+\sigma_{\mathrm{ij}}e^{\omega_{\mathrm{ij}}\mathbf{D}_{\mathrm{ij}}}\nu_{\mathrm{ij}}\right)\mathbf{X}_{\mathbf{ij}}\right]}}, \tag{7}$$

where notations and symbols have been represented in equations (1)–(3) and $N$ represents the number of draws used for individual observations.

## 4. Temporal Stability and Transferability Tests

As shown in Table 3, the LRT statistic value based on equation (4) obtained by using the estimated parameters of the 2017 IAC model using the data of the 2018 IAC is 32.18, with 10 degrees of freedom. Above all, both the two tables show that the assumption that significant parameters generated by test statistics in different years are equal can be rejected in all models, with confidence >99.00%.

Concerning the global test based on equation (5), the test statistics are 149.32 and 570.268, respectively, for IAC and NIAC, and the degrees of freedom are 8 and 30, respectively. The results also indicate that the initial hypothesis that the same significant parameters in the separate IAC and NIAC models is rejected with a confidence of >99.99%. In general, the above two LRTs indicate that crash IAC and NIAC both stay temporally unstable, which is consistent with most relevant research results [29, 33, 37].

The test statistics for 2017, 2018, and 2019 are 176.27, 162.36, and 126.81, respectively, and the degrees of freedom are 18, 17, and 12, respectively. These results also indicate that within the >99.99% confidence interval, the same initial hypothesis of weekday and weekend crash models in different years can be rejected.

Considering the temporal variability, the probability difference (mean value) between the OOSP and the original model is shown in Tables 5 and 6. The IAC and NIAC model's parameters are respectively used to predict the crash data for the next year. Table 5 indicates that using the IAC

Table 5: Probability difference between different years based on the IAC model.

| Prediction year<br>Base year | IAC | | | | | |
|---|---|---|---|---|---|---|
| | 2018 | | | 2019 | | |
| | No injury | Minor injury | Severe injury | No injury | Minor injury | Severe injury |
| 2017 | 0.0118 | −0.0053 | −0.0065 | 0.0056 | −0.0029 | −0.0027 |
| 2018 | — | — | — | −0.0175 | 0.0089 | 0.0086 |

Table 6: Probability difference between different years based on the NIAC model.

| Prediction year<br>Base year | NIAC | | | | | |
|---|---|---|---|---|---|---|
| | 2018 | | | 2019 | | |
| | No injury | Minor injury | Severe injury | No injury | Minor injury | Severe injury |
| 2017 | 0.0385 | −0.0124 | −0.0261 | 0.0181 | 0.0097 | −0.0278 |
| 2018 | — | — | — | −0.0156 | 0.0102 | 0.0054 |

Table 7: NAIC model is used to predict the probability difference of AIC data.

| Year | NAIC model to predict AIC data | | |
|---|---|---|---|
| | No injury | Minor injury | Severe injury |
| 2017 | 0.0129 | −0.0143 | 0.0014 |
| 2018 | 0.0126 | −0.0054 | −0.0072 |
| 2019 | 0.0174 | −0.0156 | −0.0018 |

Table 8: AIC model is used to predict the probability difference of NAIC data.

| Year | IAC model to predict NAIC data | | |
|---|---|---|---|
| | No injury | Minor injury | Severe injury |
| 2017 | 0.0095 | 0.0049 | −0.0144 |
| 2018 | 0.0025 | 0.0079 | −0.0104 |
| 2019 | −0.0054 | 0.0148 | −0.0094 |

model parameters of 2017 to predict the IAC data of 2018 can overestimate the no injury outcome probability (0.0118) and underestimate the probability of minor/severe injury outcomes (−0.0053 and −0.0065, respectively). In addition, as shown in Table 6, the probability of no injury outcome is overpredicted when using the 2017 NIAC model to predict the 2018 NIAC data. Both the two tables also reveal the potential temporal variability between the year periods.

In addition, Table 7 lists the mean values of probability difference by using NIAC model parameters to predict IAC data, while Table 8 lists the mean values of probability difference by using estimated parameters of the IAC model to predict NIAC data. Table 7 shows that the probability of no injury outcomes is overestimated, while the likelihood of minor injury levels is underestimated, with the absolute value greater than 0.01.

## 5. Out-of-Sample Prediction

Consistent with the results based on the LRT, the results of OOSP also indicate the nontransferability between crashes in IAC and NIAC models. The OOSP of nontransferability further illustrates the difference in the generation mechanism of IAC and NIAC. Therefore, targeted recommendations need to be implemented for these two types of the crash to eliminate the injury severity of IAC and NIAC.

The recent studies indicated high degrees of probability differences [21, 25, 36], while Yan et al. [38] showed a relatively low injury effect of temporal/crash-type shifts. And Wang et al. [21] illustrated that the contradictory phenomenon could be attributed to the overall variation in the integration of the observation size, injury outcomes distribution, and determinants. The OOSP can further verify the transferable issues across the three grades based on the two-unobserved-heterogeneity models. Notably, this can also confirm the necessity of separating the expressway crashes into IAC and NIAC.

Generally, the OOSP results also provide a basis for the nontransferability among IAC and NIAC and temporal variability across different year periods.

## 6. Results and Discussion

Table 9 shows the goodness-of-fit comparison results of four models, including three basic logit models (fixed parameter logit model, random parameter logit model, and random parameter logit model with mean heterogeneity) and random parameter logit model with heterogeneity in mean and variance (RPLHMV). It should be noted from Table 9 that for different individual models, the random parameter logit model with mean and variance heterogeneity obtains higher $\rho^2$. At the same time, there are also lower AIC and BIC, specifying great improvement in the model's fit. This also demonstrates the superiority of the RPLHMV proposed in this paper.

Then, Table 10 lists the parameter estimation results based on RPLHMV, indicating an overall good fit with the $\rho^2$ values greater than 0.65. To further study the influence of significant variables in different models on injury severity, Table 11 also demonstrates the marginal effects of determinants of IAC and NIAC models. A specific difference exists in the significant variables among IAC and NIAC models, and the influencing factors of injury severity vary in different periods. Moreover, note that the influence degree

Table 9: Goodness-of-fit measures among different models.

| | Fixed parameter multinomial logit | | Random parameter logit | | Random parameter logit with heterogeneity in means | | Random parameter logit with heterogeneity in means and variances | |
|---|---|---|---|---|---|---|---|---|
| | IAC | NIAC | IAC | NIAC | IAC | NIAC | IAC | NIAC |
| *2017* | | | | | | | | |
| Number of parameters ($K$) | 6 | 19 | 6 | 20 | 6 | 20 | 6 | 20 |
| Number of observations ($N$) | 224 | 1399 | 224 | 1399 | 224 | 1399 | 224 | 1399 |
| Log-likelihood at zero (LL(0)) | −245.952 | −1536.102 | −245.952 | −1536.102 | −245.952 | −1536.102 | −245.952 | −1536.102 |
| Log-likelihood at convergence (($\beta$)) | −56.711 | −503.365 | −56.711 | −499.365 | −56.711 | −499.365 | −56.711 | −499.365 |
| $\rho^2 = 1 - \mathrm{LL}(\beta)/\mathrm{LL}(0)$ | 0.769 | 0.672 | 0.769 | 0.675 | 0.769 | 0.675 | 0.769 | 0.675 |
| Akaike information criterion (AIC) | 125.422 | 1044.730 | 125.422 | 1038.730 | 125.422 | 1038.730 | 125.422 | 1038.730 |
| Bayesian information criterion (BIC) | 145.892 | 1144.357 | 145.892 | 1143.600 | 145.892 | 1143.600 | 145.892 | 1143.600 |
| *2018* | | | | | | | | |
| Number of parameters ($K$) | 10 | 19 | 10 | 20 | 10 | 21 | 10 | 22 |
| Number of observations ($N$) | 209 | 1675 | 209 | 1675 | 209 | 1675 | 209 | 1675 |
| Log-likelihood at zero (LL(0)) | −229.482 | −1839.15 | −229.482 | −1839.15 | −229.482 | −1839.15 | −229.482 | −1839.15 |
| Log-likelihood at convergence (($\beta$)) | −74.762 | −594.635 | −74.762 | −593.254 | −74.762 | −582.326 | −74.762 | −569.698 |
| $\rho^2 = 1 - \mathrm{LL}(\beta)/\mathrm{LL}(0)$ | 0.674 | 0.677 | 0.674 | 0.677 | 0.674 | 0.683 | 0.674 | 0.690 |
| Akaike information criterion (AIC) | 169.524 | 1227.270 | 169.524 | 1226.508 | 169.524 | 1206.652 | 169.524 | 1183.396 |
| Bayesian information criterion (BIC) | 202.947 | 1330.318 | 202.947 | 1334.979 | 202.947 | 1320.547 | 202.947 | 1302.715 |
| *2019* | | | | | | | | |
| Number of parameters ($K$) | 6 | 13 | 6 | 14 | 6 | 15 | 6 | 15 |
| Number of observations ($N$) | 197 | 1500 | 197 | 1500 | 197 | 1500 | 197 | 1500 |
| Log-likelihood at zero (LL(0)) | −216.306 | −1647.304 | −216.306 | −1647.304 | −216.306 | −1647.304 | −216.306 | −1647.304 |
| Log-likelihood at convergence (($\beta$)) | −72.348 | −484.658 | −72.348 | −481.264 | −72.348 | −477.469 | −72.348 | −477.469 |
| $\rho^2 = 1 - \mathrm{LL}(\beta)/\mathrm{LL}(0)$ | 0.666 | 0.706 | 0.666 | 0.708 | 0.666 | 0.710 | 0.666 | 0.710 |
| Akaike information criterion (AIC) | 156.696 | 995.316 | 156.696 | 990.528 | 156.696 | 984.938 | 156.696 | 984.938 |
| Bayesian information criterion (BIC) | 176.395 | 1064.388 | 176.395 | 1064.913 | 176.395 | 1064.636 | 176.395 | 1064.636 |
| *2017–2019* | | | | | | | | |
| Number of parameters ($K$) | 14 | 23 | 14 | 25 | 14 | 27 | 14 | 27 |
| Number of observations ($N$) | 630 | 4574 | 630 | 4574 | 630 | 4574 | 630 | 4574 |
| Log-likelihood at zero (LL(0)) | −691.74 | −5022.252 | −691.74 | −5022.252 | −691.74 | −5022.252 | −691.74 | −5022.252 |
| Log-likelihood at convergence (($\beta$)) | −129.161 | −1275.649 | −129.161 | −1269.516 | −129.161 | −1261.398 | −129.161 | −1261.398 |
| $\rho^2 = 1 - \mathrm{LL}(\beta)/\mathrm{LL}(0)$ | 0.813 | 0.746 | 0.813 | 0.747 | 0.813 | 0.749 | 0.813 | 0.749 |
| Akaike information criterion (AIC) | 286.322 | 2597.298 | 286.322 | 2589.032 | 286.322 | 2576.796 | 286.322 | 2576.796 |
| Bayesian information criterion (BIC) | 348.562 | 2745.145 | 348.562 | 2749.736 | 348.562 | 2750.356 | 348.562 | 2750.356 |

and trend of the same determinants will change across the year and by other crash areas.

*6.1. Driver Characteristics.* The driver's improper operation is identified to affect minor injury in the 2017 NIAC model, and negative values showed that improper operation reduced the minor injury likelihood. For example, the marginal effect values in Table 11 showed that improper operation reduced the minor injury possibilities by 0.0078, while the no injury likelihood increased by 0.0076. However, overspeed does not show significance in all models.

*6.2. Vehicle Characteristics.* The single-vehicle indicator significantly affects no injury in the 2019 NIAC model and significantly influences severe injury in the 2017 IAC model. In addition, the estimation parameters of single-vehicle crashes specific to severe injury in the 2018 IAC model are identified to be statistically random. The corresponding normal distribution of $N(-6.502, 4.809)$ means that 91.2% of single-vehicle crashes in 2018 are less likely to involve severe injuries, while another 8.8% tend to have severe injuries.

The two-vehicle crash only has a negative correlation with minor injury outcomes in 2017 NIAC. The marginal effect values in Table 11 show that this variable increases the no injury and severe injury likelihood by 0.0227 and 0.0018, respectively, and decreases the minor injury likelihood results by 0.0245. The difference in the operating speed of two vehicles might be greater, which increases greater impact force and the outcomes of crashes [39]. Moreover, multi-vehicle crash decreases the minor injury likelihood in the 2017 NIAC and 2018 IAC models, indicating the increased minor injury likelihood in the 2018 IAC and severe injury likelihood in the 2017 IAC. The value of marginal effect shows that this variable presents inconsistent effects on minor injuries. To be specific, the probability of minor injury likelihood decreases in the 2017 IAC model, while it increases in the other three models. However, consistent findings exist in the other two injury outcomes, such as a declined likelihood of no injuries and rising severe injury

Table 10: The results of IAC and NIAC models based on random parameter logit model with heterogeneity in mean and variance.

| Variable | 2017 | | 2018 | | 2019 | | 2017–2019[1] | |
|---|---|---|---|---|---|---|---|---|
| | IAC | NIAC | IAC | NIAC | IAC | NIAC | IAC | NIAC |
| [MI][2] constant | −0.251 (−2.98) | −1.206 (−4.40) | −1.655 (−2.91) | −2.451 (−5.07) | 3.462 (2.72) | −2.803 (−2.81) | −0.853 (−2.66) | 1.561 (4.00) |
| [SI] constant | −6.256 (−2.75) | −3.103 (−2.25) | −5.501 (−5.51) | −1.667 (−2.89) | −6.632 (−4.59) | −5.73 (−7.36) | −4.425 (−6.94) | −0.306 (−3.45) |
| *Driver characteristics* | | | | | | | | |
| [MI] improper action (1 if improper action, 0 otherwise) | | −0.626 (−2.82) | | | | | | −3.511 (−3.67) |
| *Vehicle characteristics* | | | | | | | | |
| [NI] single-vehicle indicator (1 if the number of vehicles involved in the crash is 1, 0 otherwise) | | | | | | 2.516 (4.15) | | |
| [SI] single-vehicle indicator (1 if the number of vehicles involved in the crash is 1, 0 otherwise) | | −1.037 (−2.16) | | | | | | −0.803 (−2.90) |
| [MI] two-vehicle indicator (1 if the number of vehicles involved in the crash is 2, 0 otherwise) | | −1.100 (−3.60) | | | | | | |
| [NI] multivehicle indicator (1: the total number of vehicles in the crash is more than 2, otherwise 0) | | −0.957 (−2.83) | −1.489 (−2.00) | | | | | |
| [MI] multivehicle indicator (1: the total number of vehicles in the crash is more than 2, otherwise 0) | | | | 1.136 (3.93) | | | | 1.813 (2.93) |
| [SI] multivehicle indicator (1: the total number of vehicles in the crash is more than 2, otherwise 0) | 3.201 (2.57) | | | | | | 1.391 (2.62) | |
| [SI] passenger car (1 if the passenger car involved in crash, otherwise 0) | | | | | | | | −0.323 (−2.59) |
| [MI] minibus (1 if the van involved in crash, otherwise 0) | | | | | | 1.304 (2.51) | | |
| [NI] bus (1 if the bus involved in crash, otherwise 0) | | | | −0.818 (−2.90) | | | | |
| [NI] van (1 if the minibus involved in crash, otherwise 0) | | | | | | | −1.934 (−1.98) | |
| [SI] van (1 if the minibus involved in crash, otherwise 0) | | | | 1.295 (2.59) | | | | |
| [MI] truck (1 if the truck involved in crash, otherwise 0) | | | 1.591 (2.00) | | | | | |
| [SI] truck (1 if the truck involved in crash, otherwise 0) | | 1.478 (2.12) | | | | | −1.986 (−2.79) | −0.996 (−2.48) |
| [MI] heavy truck (1 if the heavy truck involved in crash, otherwise 0) | | | | 0.556 (2.45) | | | 0.846 (2.56) | |
| *Road characteristics* | | | | | | | | |
| [SI] $R_{present}$: radius of the horizontal curve ($10^3$ m) | | | 0.00150 (2.11) | | | | | 0.00065 (2.59) |
| [SI] $R_{back}$: radius of the plane curve of back section ($10^3$ m) | | | | | | | 0.00126 (2.30) | |
| [NI] $L_{present}$: length of the horizontal curve ($10^3$ m) | | | | | | −0.404 (−2.73) | | |
| [MI] $L_{present}$: length of the horizontal curve ($10^3$ m) | | | | 0.374 (2.24) | | | | 0.125 (2.73) |
| [SI] $Ls_{min}$: length of the longitudinal slope corresponding to the minimum grade (m) | | | | | | | | −0.00103 (−2.03) |
| [MI] $Ls_{max}$: length of the longitudinal slope corresponding to the maximum grade (m) | | −0.00116 (−2.71) | | −0.00167 (−2.58) | | | | |
| [NI] $i_{max}$: maximum longitudinal grade of current section (%) | | | | | | | 0.00383 (2.90) | |
| *Environmental characteristics* | | | | | | | | |
| [MI] fine weather (1 if weather condition is fine, 0 otherwise) | | | | | | | | −0.920 (−2.74) |
| [SI] fine weather (1 if weather condition is fine, 0 otherwise) | | 1.069 (2.18) | | | | | | |
| [MI] cloudy weather (1 if weather condition is cloudy, 0 otherwise) | | | | 0.697 (2.97) | | | | |
| [MI] rainy weather (1 if weather condition is rainy, 0 otherwise) | | | | | | | | −1.165 (−2.91) |
| [SI] rainy weather (1 if weather condition is rainy, 0 otherwise) | | | | | | 1.813 (2.28) | | |
| [MI] snowy weather (1 if weather condition is snowy, 0 otherwise) | | | | 0.829 (2.33) | | | | |
| [NI] icy surface condition (1 if surface condition is icy, 0 otherwise) | | | | | | | | 1.561 (4.00) |
| [SI] icy surface condition (1 if surface condition is icy, 0 otherwise) | | | | | 0.550 (2.16) | | | |

Table 10: Continued.

| Variable | 2017 IAC | 2017 NIAC | 2018 IAC | 2018 NIAC | 2019 IAC | 2019 NIAC | 2017–2019[1] IAC | 2017–2019[1] NIAC |
|---|---|---|---|---|---|---|---|---|
| *Temporal characteristics* | | | | | | | | |
| [SI] Monday (1: occurs on Monday, otherwise 0) | | | | 1.590 (3.53) | | | | 0.647 (2.04) |
| [NI] Tuesday (1: occurs on Tuesday, otherwise 0) | | | −1.591 (−2.45) | | | | | |
| [MI] Tuesday (1: occurs on Tuesday, otherwise 0) | | | | | | | 1.438 (2.57) | |
| [SI] Tuesday (1: occurs on Tuesday, otherwise 0) | | | | | 2.527 (2.03) | | | |
| [SI] Wednesday (1: occurs on Wednesday, otherwise 0) | | 1.187 (2.63) | | 1.050 (2.57) | | 1.639 (2.20) | | |
| [SI] early morning (1: occurs from 0 : 00 to 5 : 59, otherwise 0) | | 1.191 (2.14) | 3.105 (3.39) | 1.071 (2.92) | | | 2.568 (3.78) | 0.865 (3.25) |
| [MI] afternoon (1: occurs from 12 : 00 to 17 : 59, otherwise 0) | | −0.574 (−2.73) | | −0.662 (−2.43) | | | | |
| [SI] afternoon (1: occurs from 12 : 00 to 17 : 59, otherwise 0) | | | | | | | | −0.692 (−2.77) |
| [MI] night (1: occurs from 18 : 00–23 : 59, otherwise 0) | | | | −0.627 (−2.06) | | | | |
| [SI] night (1: occurs from 18 : 00–23 : 59, otherwise 0) | 1.548 (2.88) | 1.920 (2.59) | 2.258 (2.40) | | | | 1.497 (2.06) | |
| [NI] spring (1: occurs in spring, otherwise, 0) | | 0.431 (2.50) | | | | | | |
| [SI] spring (1: occurs in spring, otherwise, 0) | | | | | | 1.642 (2.53) | | |
| [MI] summer (1: occurs in summer, otherwise 0) | | | | | | 0.530 (2.29) | | 0.362 (2.34) |
| [NI] winter (1: occurs in winter, otherwise 0) | −2.094 (−2.98) | −0.393 (−2.78) | | | −1.829 (−2.33) | | | |
| [SI] winter (1: occurs in winter, otherwise 0) | | | | 0.732 (2.76) | | | 1.479 (2.20) | 0.551 (2.89) |
| *Traffic characteristics* | | | | | | | | |
| [SI] bridge (1: the section occurring is the bridge section, otherwise 0) | | | | | | | −1.847 (−2.26) | |
| [MI] AADT (annual mean daily traffic volume, pcu/d) | −0.000759 (−2.88) | | −0.000604 (−2.68) | | −0.000210 (−2.51) | −0.000448 (−2.77) | −0.000600 (−2.12) | |
| [SI] AADT (annual mean daily traffic volume, pcu/d) | | | | −0.000535 (−3.55) | | | | −0.000402 (−3.67) |
| *Crash characteristics* | | | | | | | | |
| [NI] sideswipe (1: the crash type is sideswipe, otherwise 0) | | | | | | −3.649 (−4.14) | | |
| [SI] sideswipe (1: the crash type is sideswipe, otherwise 0) | | 2.941 (2.55) | | | | | | |
| [SI] hit fixed object (1: the crash type is hitting fixed object, otherwise 0) | | −1.894 (−2.11) | | | | | | |
| [MI] running off the road (1: the crash type is running off the road, otherwise 0) | | | | | | 1.016 (2.15) | | |
| [MI] rollover (1: the crash type is rollover, otherwise 0) | | | | | | | | 1.048 (3.30) |
| [SI] rear-end collision (1: the crash type is rear-end collision, otherwise 0) | | | | | | | | −0.523 (−2.60) |
| [MI] other crash types (1: other crash types, otherwise 0) | | −0.781 (−2.94) | 1.440 (2.61) | | | | | |
| [SI] EMS greater than 60 minutes (1: rescue response time greater than 60 minutes, otherwise 0) | | | | 0.959 (2.45) | | | | |
| *Random parameter (normally distributed)* | | | | | | | | |
| [MI] over speed (1: the driver is speeding, otherwise 0) | | | | | | | | −3.286 (−2.97) |
| *Standard deviation* | | | | | | | | 1.381 (2.20) |
| [SI] single-vehicle indicator (1 if the number of vehicles involved in the crash is 1, 0 otherwise) | | | | −6.502 (−2.89) | | | | |
| *Standard deviation* | | | | 4.809 (2.22) | | | | |
| [SI] AADT (annual mean daily traffic volume, pcu/d) | | −0.000926 (−2.22) | | | | | | |
| *Standard deviation* | | 0.318 (2.63) | | | | | | |
| [SI] $Ls_{min}$: length of the longitudinal slope corresponding to the minimum grade (m) | | | | | | −0.00463 (−1.98) | | |

Table 10: Continued.

| Variable | 2017 | | 2018 | | 2019 | | 2017–2019[1] | |
|---|---|---|---|---|---|---|---|---|
| | IAC | NIAC | IAC | NIAC | IAC | NIAC | IAC | NIAC |
| *Standard deviation* | | | | | | 0.00215 (2.31) | | |
| [MI] other crash types (1: other crash types, otherwise 0) | | | | | | | | −3.244 (−2.12) |
| *Standard deviation* | | | | | | | | 3.794 (3.35) |
| *Heterogeneity of random parameter mean* | | | | | | | | |
| [MI] over speed (1: the driver is speeding, otherwise 0): Sunday (1: occurred on Sunday) | | | | | | | | −1.233 (−2.66) |
| [SI] single-vehicle indicator (1 if the number of vehicles involved in the crash is 1, 0 otherwise): Tuesday (1: occurs on Tuesday) | | | | 4.707 (2.95) | | | | |
| [SI] $Ls_{min}$: length of the longitudinal slope corresponding to the minimum grade (m): early morning (1: occurs from 0 : 00 to 5 : 59, otherwise 0) | | | | | | 0.00215 (2.88) | | |
| [MI] other crash types (1: other crash types, otherwise 0): early morning (1: occurs from 0 : 00 to 5 : 59, otherwise 0) | | | | | | | | 3.794 (3.35) |
| *Heterogeneity of random parameter variance* | | | | | | | | |
| [SI] single-vehicle indicator (1 if the number of vehicles involved in the crash is 1, 0 otherwise): afternoon (1: occurs from 12 : 00 to 17 : 59) | | | | −0.343 (−2.67) | | | | |
| Number of parameters (K) | 6 | 20 | 10 | 22 | 6 | 15 | 14 | 27 |
| Number of observations (N) | 224 | 1399 | 209 | 1675 | 197 | 1500 | 630 | 4574 |
| Log-likelihood at zero (LL (0)) | −245.952 | −1536.102 | −229.482 | −1839.15 | −216.306 | −1647.304 | −691.74 | −5022.252 |
| Log-likelihood at convergence ($(\beta)$) | −56.711 | −499.365 | −74.762 | −569.698 | −72.348 | −477.469 | −129.161 | −1261.398 |
| $\rho^2 = 1 - LL(\beta)/LL(0)$ | 0.769 | 0.675 | 0.674 | 0.690 | 0.666 | 0.710 | 0.813 | 0.749 |
| Akaike information criterion (AIC) | 125.422 | 1038.730 | 169.524 | 1183.396 | 156.696 | 984.938 | 286.322 | 2576.796 |
| Bayesian information criterion (BIC) | 145.892 | 1143.600 | 202.947 | 1302.715 | 176.395 | 1064.636 | 348.562 | 2750.356 |

*Note.* [1]To better explore the structural fracture and temporal variation in the estimated results, the overall combined data of the year 2017–2019 were used as a reference, covering three years of IAC and NIAC, respectively. [2]It represents significant effects on MI, where NI represents no injury, MI represents minor injury, and SI represents severe injury.

Table 11: The marginal effect of significance variables in IAC and NIAC based on random parameter logit model with heterogeneity in mean and variance.

| Variable | No injury 2017 | No injury 2018 | No injury 2019 | Minor injury 2017 | Minor injury 2018 | Minor injury 2019 | Severe injury 2017 | Severe injury 2018 | Severe injury 2019 |
|---|---|---|---|---|---|---|---|---|---|
| *Driver characteristics* | | | | | | | | | |
| Improper action (1 if improper action, 0 otherwise) | −(0.0076) | | | −(−0.0078) | | | −(0.0002) | | |
| *Vehicle characteristics* | | | | | | | | | |
| Single-vehicle indicator (1 if the number of vehicles involved in the crash is 1, 0 otherwise) | −(0.0104) | −(0.0112) | −(0.0208) | −(0.0015) | −(0.0010) | −(−0.0064) | −(−0.0119) | −(−0.0122) | (−0.0144) |
| Two-vehicle indicator (1 if the number of vehicles involved in the crash is 2, 0 otherwise) | −(0.0227) | | | −(−0.0245) | | | −(0.0018) | | |
| Multivehicle indicator (1: the total number of vehicles in the crash is more than 2, otherwise 0) | −0.0191 (−0.0097) | −0.0236 (−0.0134) | | −0.0007 (0.0071) | 0.0185 (0.0126) | | 0.0198 (0.0026) | 0.0050 (0.0008) | |
| Minibus (1 if the van involved in the crash, otherwise 0) | | | −(−0.0037) | | | −(0.0038) | | | −(−0.0001) |
| Bus (1 if the bus involved in crash, otherwise 0) | | −(−0.0035) | | | −(0.0025) | | | −(0.0010) | |
| Van (1 if the minibus involved in crash, otherwise 0) | | −(−0.0018) | | | −(−0.0002) | | | −(0.0020) | |
| Truck (1: the truck involved in crash, otherwise 0) | −(−0.0045) | −0.0234 (−) | | −(−0.0010) | 0.0256 (−) | | −(0.0055) | −0.0022 (−) | |
| Heavy truck (1: the heavy truck involved in crash, otherwise 0) | | −(−0.0121) | | | −(0.0131) | | | −(−0.0010) | |
| *Road characteristics* | | | | | | | | | |
| $R_{\text{present}}$: radius of the horizontal curve ($10^3$ m) | | −0.0480 (−) | | | −0.0053 (−) | | | 0.0533 (−) | |
| $L_{\text{present}}$: length of the horizontal curve ($10^3$ m) | | −(−0.0462) | −(−0.0166) | | −(0.0484) | −(0.0215) | | −(−0.0022) | −(−0.0049) |
| $\text{Ls}_{\text{min}}$: length of the longitudinal slope corresponding to the minimum grade (m) | | | −(0.0053) | | | −(0.0004) | | | −(−0.0057) |
| $\text{Ls}_{\text{max}}$: length of the longitudinal slope corresponding to the maximum grade (m) | −(0.0200) | −(0.0642) | | −(−0.0206) | −(−0.0673) | | −(0.0006) | −(0.0031) | |
| *Environmental characteristics* | | | | | | | | | |
| Sunny (1: the weather is sunny, otherwise 0) | −(−0.0039) | | | −(−0.0006) | | | −(0.0045) | | |
| Cloudy (1: the weather is cloudy, otherwise 0) | | −(−0.0223) | | | −(0.0232) | | | −(−0.0009) | |
| Rainy (1: the weather is rainy, otherwise 0) | | | −(−0.0040) | | | −(−0.0002) | | | −(0.0042) |
| Snowy (1: the weather is snowy, otherwise 0) | | −(−0.0055) | | | −(0.0058) | | | −(−0.0003) | |
| Icy road (1: the road is icy, otherwise 0) | | | −0.0098 (−) | | | −0.0001 (−) | | | 0.0099 (−) |
| *Time characteristics* | | | | | | | | | |
| Monday (1: occurs on Monday, otherwise 0) | | −(−0.0084) | | | −(−0.0012) | | | −(0.0096) | |
| Tuesday (1: occurs on Tuesday, otherwise 0) | | −0.0298 (−) | −0.0147 (−) | | 0.0136 (−) | −0.0002 (−) | | 0.0162 (−) | 0.0149 (−) |
| Wednesday (1: occurs on Wednesday, otherwise 0) | −(−0.0081) | −(−0.0072) | −(−0.0066) | −(−0.0010) | −(−0.0009) | −(−0.0003) | −(0.0091) | −(0.0081) | −(0.0069) |
| Early morning (1: occurs from 0 : 00 to 5 : 59, otherwise 0) | −(−0.0246) | −0.0719 (−0.0125) | | −(−0.0035) | −0.0100 (−0.0018) | | −(0.0281) | 0.0819 (0.0143) | |
| Afternoon (1: occurs from 12 : 00 to 17 : 59, otherwise 0) | −(0.0056) | −(0.0098) | | −(−0.0057) | −(−0.0100) | | −(0.0001) | −(0.0002) | |
| Night (1: occurs from 18 : 00–23 : 59, otherwise 0) | −0.0211 (−0.0090) | −0.0354 (0.0060) | | −0.0023 (−0.0010) | −0.0047 (−0.0062) | | 0.0235 (0.0100) | 0.0402 (0.0002) | |
| Spring (1: occurs in spring, otherwise, 0) | −(0.0074) | | −(−0.0083) | −(−0.0061) | | −(−0.0004) | −(−0.0013) | | −(0.0087) |
| Summer (1: occurs in summer, otherwise 0) | | | −(−0.0046) | | | −(0.0044) | | | −(0.0002) |

TABLE 11: Continued.

| Variable | No injury | | | Minor injury | | | Severe injury | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2017 | 2018 | 2019 | 2017 | 2018 | 2019 | 2017 | 2018 | 2019 |
| Winter (1: occurs in winter, otherwise 0) | −0.0703 (−0.0121) | −(−0.0051) | −0.0056 (−) | 0.0474 (0.0085) | −(−0.0006) | 0.0041 (−) | 0.0229 (0.0036) | −(0.0057) | 0.0015 (−) |
| *Traffic characteristics* | | | | | | | | | |
| AADT (annual mean daily traffic volume, pcu/d) | 0.1504 (0.0961) | 0.1657 (0.0713) | 0.0983 (0.0599) | −0.1425 (−0.0848) | −0.1493 (−0.0082) | −0.0974 (−0.0589) | −0.0079 (−0.0113) | −0.0165 (−0.0631) | −0.0009 (−0.0010) |
| *Crash characteristics* | | | | | | | | | |
| Sideswipe (1: the crash type is sideswipe, otherwise 0) | −(−0.0012) | | −(−0.0076) | −(−0.0001) | | −(0.0066) | −(0.0013) | | −(0.0010) |
| Hit fixed object (1: the crash type is hitting fixed object, otherwise 0) | −(0.0027) | | | −(0.0004) | | | −(−0.0031) | | |
| Rear-end collision (1: the crash type is rear-end collision, otherwise 0) | | | −(−0.0055) | | | −(0.0056) | | | −(−0.0001) |
| Other crash types (1: other crash types, otherwise 0) | −(0.0196) | −0.0705 (−) | | −(−0.0206) | 0.0790 (−) | | −(0.0010) | −0.0085 (−) | |
| EMS greater than 60 minutes (1: rescue response time greater than 60 minutes, otherwise 0) | | −(−0.0154) | | | −(−0.0020) | | | −(0.0174) | |

Marginal effects of NIAC are in parentheses.

likelihood. This finding is consistent with recent studies [15, 40], indicating that the number of vehicles in the crashes tends to increase the injury severity levels.

Concerning vehicle types, minibus increases the minor injury likelihood in the 2019 NIAC model, while bus decreases the no injury likelihood in the 2018 NIAC model. In 2018 NIAC, van is positively correlated with serious injury outcomes, and marginal effects show that van improves the probability of severe injury outcomes while decreasing the no/minor injury likelihood. The truck is positively linked to minor and severe injuries in the 2018 IAC and 2017 NIAC models, respectively. The great vehicle sizes, power, and worse braking performance of trucks might produce severe outcomes of the crashes, and impose greater hazards due to the stronger crash tendency of trucks [41]. However, the marginal effect shows that truck makes different impacts on injury severity results in the two models. In contrast, truck increases the minor injury likelihood by 0.0256 in 2018 IAC and decreases the severe injury likelihood by 0.0022. In contrast, truck decreases the minor injury likelihood by 0.0010 and increases the likelihood of severe injuries by 0.0055 in the 2017 NIAC model. This may be because in interchange areas, cars tend to run at a lower speed, and the speed difference between trucks and cars is decreased, thus weakening the crash consequence. Also, the speed variation between cars and trucks in noninterchange areas is larger, increasing the injury outcomes of crashes.

In 2018, heavy trucks in noninterchange areas were positively correlated with minor injuries, and the marginal effect showed that the minor injury likelihood increased by 0.0131. The possible reason might be the fact that the maneuverability and braking performance of heavy trucks are relatively poor. In general, the car driver may be negligent and misestimate the safety distance between the car and the truck, resulting in rear-end collisions [15].

*6.3. Roadway Characteristics.* For roadway attributes, the significant variables that affect injury severity mainly include $R_{\text{present}}$, $L_{\text{present}}$, $\text{Ls}_{\text{min}}$, and $\text{Ls}_{\text{max}}$. Among them, $R_{\text{present}}$ is positively correlated with severe injury likelihood in the 2018 IAC model. The marginal effect shows that when the horizontal curve radius of this road section increases by 1%, the severe injury likelihood increases by 0.0533. The possible explanation is that the greater the horizontal curve radius is, the drivers are more inclined to a higher operating speed, and the probability of all kinds of crashes occurring in the interchange area is higher.

$L_{\text{present}}$ not only decreases the no injury likelihood in the 2019 NIAC model but also increases the minor injury likelihood in the 2018 NIAC. The marginal effect shows that this variable is consistent among the two models, specifically as it increases the minor injury possibilities and decreases the no injury/severe injury likelihood.

$\text{Ls}_{\text{max}}$ is negatively correlated with the possibility of minor injuries in noninterchange area crashes in 2017 and 2018. Marginal effects show that with a 1% increase in $\text{Ls}_{\text{max}}$, the minor injury likelihood in NIAC decreased by 0.0206 and 0.0673, respectively, in 2017 and 2018, while the no/severe injury likelihood increased correspondingly. Previous studies have shown that steeper slopes indicate a shorter line of sight, so the drivers have a shorter time to react appropriately to the upcoming crash [42–44]. Another explanation may be the driver's compensation mechanism for potential risks. Due to the reduced sight distance, drivers tend to operate more cautiously and conservatively and eliminate injury severity outcomes obviously [45].

In addition, $\text{Ls}_{\text{min}}$ is identified as a significant random parameter on the results of severe injury in the 2019 NIAC model. Also, the normal distribution of $N$ (−0.00463, 0.00215) indicates that 98.3% of 2019 NIAC tends to decrease the severe injury likelihood with increased $\text{Ls}_{\text{min}}$ and increase the severe injury likelihood for another 1.7% of observations.

*6.4. Environmental Characteristics.* For environmental characteristics, sunny, cloudy, rainy, snowy, and icy roads are significant in the models. Among them, all the other weather parameters are effective only in the NIAC models, except for the icy road in the 2019 IAC model. In the 2019 IAC model, icy road increases the severe injury likelihood by 0.0099.

There is a positive correlation between sunny weather and severe injury in the 2017 NIAC model, while the marginal effects demonstrate that the extreme injury likelihood increases by 0.0045 on sunny days. In addition, both cloudy and snowy days are positively relevant to minor injury outcomes in the 2018 NIAC model, and the marginal effects show that cloudy and snowy days increase the minor injury likelihood by 0.0232 and 0.0058, respectively. However, rainy weather is positively correlated with severe injury in the 2019 NIAC model, increasing the severe injury likelihood by 0.0042. Moreover, some recent studies argue more minor and severe injuries during poor weather conditions [14, 46, 47], while other research efforts indicate contradictory findings [17].

*6.5. Temporal Characteristics.* Monday is positively correlated with severe injuries in the 2018 NIAC model. Tuesday is negatively correlated with no injuries in the 2018 NIAC model and positively correlated with severe injuries in the 2019 IAC model. The results indicate the temporal variation of the two variables to some extent. At the same time, Wednesday shows a positive correlation with the severe injuries in NIAC for the three years, while it was not significant in the NIAC models, revealing the nontransferability of crash occurring among the two different areas. The marginal effect shows that the severe injury likelihood in NIAC increased by 0.0069 to 0.0091 on Wednesday.

As for the time of each day, the severe injury likelihood increases in both early morning and night time. The main reason may be poor visibility in the early morning and night, and easy fatigue or speeding driving, significantly increasing the probability of severe crash consequences [48]. For example, in the 2018 IAC model, the severe injury likelihood during early morning increases by 0.0819, while the probability only increases by 0.0143 in the 2018 NIAC model, indicating that IAC tends to involve more severe injuries in the early morning. At the same time, in the 2017 and 2018 NIAC models, the afternoon time decreases the minor injury likelihood, while the effects on severe injury are relatively small. It is mainly due to the good light and driving environment in the afternoon, so drivers are more likely to percept potential risk scenes and take effective operations to slow down or avoid collisions [45].

However, the influence trend of spring on the injury severity among 2017 and 2019 NIAC models is inconsistent. Specifically, the no injury likelihood increases by 0.0074 in 2017, while the likelihood decreases by 0.0083 in 2018, specifying the temporal variability of the influence trend to some extent. Summer is positively correlated with the probability of minor injuries only in the 2019 NIAC model. In winter, the severe injury likelihood increases in the 2017/2019 IAC models and 2017/2018 NIAC models, indicating more severe injuries during winter. The main explanation might be that the crashes occurred in Jiangsu Province, where the average temperature in winter is close to zero, resulting in frequent icing on the road in winter, aggravating the injury severity outcomes. Moreover, the adverse weather conditions during these months could affect the driver perception reaction time, especially under snow and rain weather [49].

*6.6. Traffic Characteristics.* AADT (annual average daily traffic volume) shows a normal effect across all models, declining the probability of minor and severe injuries while rising the no injury likelihood. This finding is consistent with previous studies because increasing traffic volume reduces the driving speed of vehicles [42, 45]. However, high-speed vehicles can lead to serious consequences of crashes.

Interestingly, certain differences exist in the degree of effects between IAC and NIAC models. For example, the degree of impact of AADT in the interchange area is greater than that in the noninterchange area. Specifically, when AADT increases by 1%, the decreased probability of severe injuries in IAC is 1.1–2.3 times compared to that in NIAC.

*6.7. Crash Characteristic.* Sideswipe type significantly affects severe and minor injuries in the 2017 and 2019 NIAC models, respectively. The marginal effect shows that this crash type decreases the no injury likelihood and increases the severe injury likelihood among both models. However, in the 2017 NIAC model, a negative correlation exists between hitting fixed objects and severe injury outcomes. The marginal effect indicated that hitting fixed objects decreases the severe injury likelihood by 0.0031. On the other hand, off-road crashes were positively correlated with minor injury results in 2019 NIAC.

Interestingly, other crash types were negatively and positively correlated with minor injuries among the 2017 NIAC and 2018 IAC models, respectively. However, the marginal effects were utterly opposite in three injury severity levels. Specifically, the severe injury likelihood in other crashes in the IAC decreased by 0.0085 in 2018, while the severe injury likelihood in NIAC increased by 0.0010 in 2017.

For the rescue response time, the rescue response time exceeding 60 minutes increases the probability of severe injury in the 2018 NIAC model, and the marginal effect value is 0.0174.

*6.8. Heterogeneity in Mean and Variance.* It can be found from the model results that among the crashes in the 2018 NIAC model, the parameter on Tuesday increases the mean value of the random parameter single-vehicle crash by 4.707, indicating an increased likelihood of severe injuries when single-vehicle crashes occur on Tuesday. At the same time, the mean value of the random parameter $Ls_{min}$ in 2019 NIAC increased by 0.00215 in the early morning. The severe injury likelihood increases in road sections with large $Ls_{min}$ in NIAC. This also reveals the potential relationship between the $Ls_{min}$ and early morning, further indicating that the severe injury likelihood increases in the early morning time.

In terms of the heterogeneity of random parameter variance, afternoon decreases the variance of the random parameter single-vehicle in the 2018 NIAC model by 0.343, indicating that, in 2018, the afternoon likelihood of single-vehicle crashes with severe injuries in noninterchange areas decreased. The results could be further evidence of better visibility and driving conditions during afternoon.

The mean and variance of random parameters only exist in the NIAC model. These heterogeneities improve the fit in goodness degree and estimation accuracy of the model to some certain extent. Then, they capture the potential influences between parameters and reveal the degree of influence of the correlation between the two parameters on the injury severity outcomes.

*6.9. Practical Implications.* To show the differences in the determinants, Table 12 compares the determinants showing the differences in temporal shifts and crash areas. These results have specific guiding recommendations for the safety measures and decision-making of road designers and traffic management departments, and the safety improvement strategies among interchange areas and noninterchange areas could be proposed as follows:

(1) During the early morning and night time, it is recommended to set up active luminous warning messages, speed limit signs, and other reasonable measures. These measurements could prevent drivers from speeding or fatigued driving, especially in the interchange entrance and exit areas.

(2) In addition, educational programs should be set up to enhance safe driving.

(3) Traffic management agencies should intensify efforts to strictly strengthen the punishment and law enforcement of dangerous driving behavior.

(4) Necessary exit signs should be set at appropriate locations to ensure that drivers have enough time to change lanes, such as setting solid lane change lines

Table 12: Comparison of determinants in IAC and NIAC.

| Variable | IAC | NIAC | Detailed information |
|---|---|---|---|
| *Driver characteristics* | | | |
| Improper action | — | 2017 | Temporal instability and nontransferability |
| *Vehicle characteristics* | | | |
| Single-vehicle indicator | — | 2017/2018/2019 | Nontransferability |
| Two-vehicle indicator | — | 2017 | Temporal instability and nontransferability |
| Multivehicle indicator | 2017/2018 | 2017/2018 | Temporal instability, this variable increases higher likelihood of severe injuries in IAC models than in NIAC models |
| Minibus | — | 2019 | Temporal instability and nontransferability |
| Bus | — | 2018 | Temporal instability and nontransferability |
| Van | — | 2018 | Temporal instability and nontransferability |
| Truck | 2018 | 2017 | Temporal instability and nontransferability |
| Heavy truck | — | 2018 | Temporal instability and nontransferability |
| *Roadway characteristics* | | | |
| $R_{\text{present}}$ | 2018 | — | Temporal instability and nontransferability |
| $L_{\text{present}}$ | — | 2018/2019 | Temporal instability and nontransferability |
| $\text{Ls}_{\text{min}}$ | — | 2019 | Temporal instability and nontransferability |
| $\text{Ls}_{\text{max}}$ | — | 2017/2018 | Temporal instability and nontransferability |
| *Environmental characteristics* | | | |
| Sunny | — | 2017 | Temporal instability and nontransferability |
| Cloudy | — | 2018 | Temporal instability and nontransferability |
| Rainy | — | 2019 | Temporal instability and nontransferability |
| Snowy | — | 2018 | Temporal instability and nontransferability |
| Icy road | 2019 | — | Temporal instability and nontransferability |
| *Temporal characteristics* | | | |
| Monday | — | 2018 | Temporal instability and nontransferability |
| Tuesday | 2018/2019 | — | Temporal instability and nontransferability |
| Wednesday | — | 2017/2018/2019 | Nontransferability |
| Early morning | 2017/2018/2019 | 2018 | Temporal instability. The effect on severe injuries in the early morning time in the 2019 NIAC model is almost 10 times higher than that in the 2018 IAC model |
| Afternoon | — | 2017/2018 | Temporal instability and nontransferability |
| Night | 2017/2018 | 2017/2018 | Temporal instability. The effects on severe injuries in the NIAC model are significantly higher than those in the IAC model |
| Spring | — | 2017/2019 | Temporal instability and nontransferability |
| Summer | — | 2019 | Temporal instability and nontransferability |
| Winter | 2017/2019 | 2017/2018 | Temporal instability |
| *Traffic characteristics* | | | |
| AADT | 2017/2018/2019 | 2017/2018/2019 | Temporal stability and transferability |
| *Crash characteristics* | | | |
| Sideswipe | — | 2017/2019 | Temporal instability and nontransferability |
| Hit fixed object | — | 2017 | Temporal instability and nontransferability |
| Rear-end collision | — | 2019 | Temporal instability and nontransferability |
| Other crash types | 2018 | 2017 | Temporal instability and nontransferability |
| EMS greater than 60 minutes | — | 2018 | Temporal instability and nontransferability |

or oscillating lines in front of the on-ramp to control random lane-changing behaviors strictly.

(5) Stricter enforcement measures should be raised to prevent random lane changes, especially at interchange entrance and exit areas.

(6) For the snow and icy roads in winter, appropriate facilities such as a monitoring system, speedometer, and audio warning system should be added to remind drivers to pay attention to the slippery road surface and reduce the operating speed to improve highway safety.

(7) Separate lanes should be implemented for cars and trucks to decrease the interaction among cars and trucks and eliminate the injury severity outcomes of the crashes.

(8) During the roadway designing, the horizontal and vertical alignments of the coordination curve should be optimized to have continuous coordination of the road in the three-dimensional geometric parameters.

## 7. Conclusions

Based on crash data from the Beijing–Shanghai Expressway across three years (2017–2019), this study analyzes the differences between crashes in interchange and noninterchange areas, along with the temporal shifts in the determinants affecting the injury severity levels. Based on this study, the following conclusions are summarized:

(1) By comparing with the other three basic logit models (fixed parameter logit model, the random parameter logit model, and the random parameter logit model with heterogeneity in mean), the RPLMHMV is adopted with better fit in goodness and simulation accuracy. Then, severe injury, minor injury, and no injury are considered to identify the significant variables among the driver, vehicle, roadway, environmental, temporal, traffic, and crash characteristics.

(2) The LRT and OOSP demonstrate the effects of variables vary significantly across year periods and crash areas. In addition, model results and marginal effects also show that significant parameters, corresponding influence trends, and degrees are different in different individual models. For example, although the early morning and AADT have the same influence trend, specific differences exist in influence degree. Moreover, the models' results show certain differences in the risk factors among IAC and NIAC models.

(3) Future research will be conducted based on more expressways or regions to reveal the general evaluation of crash outcomes in the different areas of China. However, generally, the current finding could help expressway designers and decision-makers understand the contributing mechanism to raise proper management strategies and enforcement countermeasures to eliminate the injury severity outcomes targeted at the interchange and noninterchange areas.

(4) Some limitations exit in the current study has limitations, including the missing variables concerning demographic characteristics that might lead to unobserved heterogeneity. Then, the data sample was small, for it was collected from two freeways. The crash data from more freeways could be collected to explore more accurate estimated results. Moreover, it is noted that the crash number for interchange areas is limited compared to that for noninterchange areas. More exploration would be conducted based on more detailed dataset by proposing advanced approaches.

## Data Availability

The data in this paper are confidential, and the readers could apply for usage through mail based on reasonable ground.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Authors' Contributions

All authors reviewed the results and approved the final version of the manuscript.

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