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Severity Analysis of Multi-Truck Crashes on Mountain Freeways Using a Mixed Logit Model

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Abstract: Many studies have analyzed the road characteristics that affect the severity of truck crashes. However, most of these studies have only examined road alignment or grade separately, without considering their combined effects. The purpose of this article is to address this gap in the literature. Our study uses truck crash data from 2015 to 2019 on freeways in the Yunnan Province of China, where the severity levels of the crashes were determined by taking into account economic loss and the number of injuries and fatalities. Our study develops three models to examine the severity of truck crashes: a multinomial logit model, a mixed logit model, and a generalized ordered logit model. The findings suggest that the mixed logit model, which can suffer from unobserved heterogeneity, is more suitable because of the higher pseudo-R-squared (ρ^2) value and lower Akaike Information Criterion and Bayesian Information Criterion. The estimation results show that the combination of curve and slope significantly increases the severity of truck crashes compared to curves and slopes alone. In addition, risk factors such as crash type, vehicle type, surface condition, time of day, pavement structure, and guardrails have a significant impact on the severity of truck crashes on mountainous freeways. Based on these findings, we developed policy recommendations for reducing the severity of multi-truck collisions on mountainous highways and improving transport sustainability. For example, if possible, the combination of curve and slope should be avoided. Additionally, it is recommended that trucks use tires with good heat resistance.

Keywords: injury severity; truck crashes; mountain freeways; curved slope combination; mixed logit

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1. Introduction

Trucking is an important part of freight movement and economic development [1]. In the past decade, the number of truck crashes on freeways has continuously increased. According to the statistics released by the Ministry of Transport of the People's Republic of China in 2021 [2], as of the end of 2020, there were 11.1 million registered trucks with a total weight of 157.8 million tons. Compared with the same period in 2019, the number of trucks and their total weight have increased significantly, by 2.06% and 16.17%, respectively. Moreover, improving road safety is an important means of enhancing transportation sustainability [3]. In this context, many studies have been conducted to identify the factors that affect the severity of truck crashes.

The mechanisms of single-vehicle (SV) crashes and multi-vehicle (MV) crashes are fundamentally different [4]. Single-vehicle and multi-vehicle collisions are related to different types of driver errors. Specifically, single-vehicle collisions are usually caused by vehicle loss of control due to driver misconduct. On the other hand, multi-vehicle collisions are usually caused by errors made by the driver when interacting with other vehicles [5,6]. In contrast, the number of multi-vehicle collisions resulting in fatal injuries is higher than that of single-vehicle collisions [7,8]. Previous studies have determined that several factors may affect the injury severity of truck crashes [9–11]. Regarding driver characteristics, the injury severity of truck crashes has been mostly associated with driver's age, driver's

sex, license validity, and drunken driving, among others [12,13]. Crash characteristics are important factors affecting the severity of crashes. Truck crashes cause more severe injuries compared to normal vehicle crashes. Therefore, crash characteristics are especially important in truck crashes. The crash characteristics that most strongly influence the severity of truck crash injuries are crash type and number of vehicles. Truck characteristics include the specific characteristics of the truck in collision, such as the size of the truck and the type of goods. Regarding environmental characteristics, the injury severity of truck crashes has been mostly associated with the time of day, weather conditions, day of the week, and surface conditions [14–16]. In terms of road characteristics, the injury severity of truck collisions is mainly related to alignment, grade, barrier, guardrail presence, road class type, number of lanes, and traffic volume [17,18].

Many studies have indicated that road characteristics play an important role in the severity of truck crashes [19–21]. These studies determined how factors, including the number of lanes, speed limit, lane width, shoulder width, and traffic volume, impact the injury severity of truck crashes. Wang and Prato [10] used data of truck crashes from 2006 to 2015 in the Jiangxi Province of China to study the interaction between geometric factors, including radius of curve, angles of deflection, and type of vertical curve, and the injury severity of truck crashes. Wen et al. [22] studied the causal factors of the severity of truck collisions on mountainous highways and found that mountainous highways are limited by topography. The road characteristics have a more significant impact on the severity of injuries. Molan, Moomen, and Ksaibati [23] revealed a strong link between the traffic barrier factors, including lateral offset, system height, and post-Spacing, and the injury severity of the crash [24]. A link between the lane width and the injury severity of truck crashes was established. Dong [4] showed connections between the length of road segment and the crash type. Dong [25] showed that pavement and gravel shoulders may affect the severity of truck crashes. Most of these studies focused on urban road and rural road sections [26,27].

Due to the limitations of topography and road geometry in mountainous regions, "sharp turns", "continuous long downhills", and "multi-tunnel sections" are common. The results have shown that crash rates on mountain freeways are generally higher than those in other regions [28]. Mountain freeways often have steep grades and sharp curves, and driver behavior and vehicle performance are quite different compared to those on non-mountain freeways. More importantly, due to topographical constraints, there are more curves and slope sections on mountain freeways, resulting in a higher risk of crashes, especially for trucks of a larger size and carrying vast loads. Ahmed [27] determined that road geometry can have a significant impact on injury severity by analyzing truck crash data. Osman [29] revealed that poor visibility on curved roads is an important reason for higher injury severity. Hosseinpour [30] showed that, in downhill sections, trucks are more likely to produce excessive heat due to continuous braking, resulting in brake failure. However, few articles have studied the combination of curve and slope.

From a methodological perspective [12,31–34], the multinomial logit model is popular in the analysis of injury severity because it has a separate function for each injury severity level. However, it has limitations due to IIA assumption and may suffer from unobserved heterogeneity. Under the framework of the multinomial logit model, a mixed logit model can overcome this problem. It is possible to induce individual heterogeneity by revising the coefficient with a probabilistic distribution. Another common logit model is the ordered logit model. With regard to the traditional ordered logit model, the threshold is set to a fixed value that does not change with the different injury severities of a crash. For different injury severities, various explanatory variables may have different effects on them. Generalized ordered logit overcomes this problem by relaxing the restriction of the proportional odds assumption.

The objective of this research is to investigate the severity risk of a multi-vehicle truck crash on mountain freeways by using the mixed logit model, which accommodates unobserved heterogeneity effects. The following section presents the data used for this

research. In the subsequent section, the research methodology is discussed. The results are presented and elaborated in a subsequent section prior to the Conclusion section.

2. Data

A comprehensive crash database provided by traffic police departments and crash appraisal departments was adopted as the empirical data of this study, and each crash record has been calibrated by crash appraisal departments. The database used in this study consists of police-recorded crash information from 15 mountainous freeways in Yunnan Province, China. The data covers the period from 2015 to 2019. This study focuses on crashes involving at least one truck and two or more vehicles. Only crash records that meet these criteria were selected for analysis. There were 1904 multi-truck crashes on these freeway segments in the studied time period (they only count as one multi-truck crash if there were more than one truck involved in a crash, and only the first truck involved will be considered). In the dataset, three injury severity levels are recorded: severe crash (fatality and disabling injury), medium crash (evident injury and possible injury), and light crash (no injury and property damage only), which account for 7.7%, 53.4%, and 38.9%, respectively.

The truck crash dataset provides detailed information about the crashes, including crash characteristics, vehicle characteristics, road characteristics, and environment characteristics. According to this information and the factors with significant influences on crash injury severity found in previous studies [35], the exogenous variables are shown in Table 1.

Table 1. Data description for the response and binary variables.

Subtitle	Variable		Mean	S.D.
Response variable				
	Crash severity Level	2 = Severe crash 1 = Medium crash 0 = Light crash		
Explanatory variable (binary variable)				
Crash type				
	Sideswipe	1 = Sideswipe 0 = Otherwise	0.25	0.43
	Rollover	1 = Rollover 0 = Otherwise	0.08	0.28
	Head-on	1 = Head-on 0 = Otherwise	0.51	0.50
	Rear-end	1 = Rear-end 0 = Otherwise	0.11	0.32
	Hit object	1 = Hit object 0 = Otherwise	0.04	0.20
Vehicle type				
	Heavy truck	1 = Heavy truck 0 = Otherwise	0.37	0.48
	Light truck	1 = Light truck 0 = Otherwise	0.42	0.49
	Medium truck	1 = Medium truck 0 = Otherwise	0.22	0.41
Surface condition				
	Dry	1 = Dry 0 = Otherwise	0.88	0.32
	Wet and snow	1 = Wet and snow 0 = Otherwise	0.12	0.32

Table 1. *Cont.*

Subtitle	Variable		Mean	S.D.
Time of day				
	Early morning	1 = Crash occurrence time is in the period from 12 a.m. to 6 a.m. 0 = Otherwise	0.09	0.29
	Morning	1 = Crash occurrence time is in the period from 6 a.m. to 12 p.m. 0 = Otherwise	0.24	0.42
	Afternoon	1 = Crash occurrence time is in the period from 12 p.m. to 6 p.m. 0 = Otherwise	0.35	0.48
	Evening	1 = Crash occurrence time is in the period from 6 p.m. to 12 a.m. 0 = Otherwise	0.29	0.45
Day of Week				
	Weekday	1 = Weekday 0 = Otherwise	0.71	0.45
	Weekend	1 = Weekend 0 = Otherwise	0.29	0.45
Season				
	Spring	1 = Spring 0 = Otherwise	0.24	0.43
	Summer	1 = Summer 0 = Otherwise	0.23	0.42
	Autumn	1 = Autumn 0 = Otherwise	0.22	0.41
	Winter	1 = Winter 0 = Otherwise	0.31	0.46
Slope combination				
	Curve and slope	1 = Slope degree $\geq$ 1% and curve radius $\leq$ 2000 m 0 = Otherwise	0.04	0.20
	Slope	1 = Slope degree $\geq$ 1% 0 = Otherwise	0.06	0.23
	Curve	1 = Curve radius $\leq$ 2000 m 0 = Otherwise	0.09	0.29
	Level straight	1 = Slope degree $\leq$ 1% and curve radius $\geq$ 2000 m 0 = Otherwise	0.81	0.39
Pavement structure				
	Asphalt	1 = Asphalt 0 = Otherwise	0.73	0.44
	Concrete	1 = Concrete 0 = Otherwise	0.21	0.41
	Dirt and sand	1 = Dirt and sand 0 = Otherwise	0.06	0.24
	Guardrail	1 = Waveform guardrail 0 = Otherwise	0.25	0.43

3. Methodology

In this section, we provide a brief introduction of all the models for examining injury severity in our research. We first introduce the generalized ordered logit model (GOL), then the multinomial logit model (MNL), and finally the mixed logit model [36].

3.1. Traditional Ordered Logit Model

As Y_i represents the ordered response taken on (0,1,2), the ordered logit model of Y_i can be represented by the following formula [37–39]:

$$Y_i^* = \alpha_i + \beta X_i + \varepsilon, i = 0, 1, 2 \tag{1}$$

$$Y_i = \begin{cases} 0, & Y_i^* \le \mu_0 \\ 1, & \mu_0 < Y_i^* \le \mu_1 \\ 2, & Y_i^* \ge \mu_1 \end{cases} \tag{2}$$

The latent preference variable Y_i* is not observed. The observed counterpart to Y_i* is Y_i. X_i is a column vector of attributes that influences the propensity associated with injury severity outcomes. α is a constant parameter for each crash severity. β is the corresponding column vector of coefficients, and ε is a random error term assumed to be identical. The probabilistic model of the ordered logit can be expressed as follows [40]:

$$P(Y_i > j) = \frac{\exp(\alpha + \beta X_i)}{1 + \exp(\alpha + \beta X_i)} \tag{3}$$

3.2. The Generalized Ordered Logit Model

The generalized ordered logit model is a flexible form of the traditional ordered model that relaxes the restriction of the proportional odds assumption [41]. The generalized ordered logit model takes into account the heterogeneous influence of the independent variables under different thresholds.

As Y_i represents the ordered response taken on (0,1,2), the generalized ordered logit model of Y_i can be represented by the following formula [42,43]:

$$Y_i^* = \alpha_i + \beta X_i + \varepsilon, i = 0, 1, 2 \tag{4}$$

$$Y_i = \begin{cases} 0, & Y_i^* \le \mu_0 X_i \\ 1, & \mu_0 X_i < Y_i^* \le \mu_1 X_i \\ 2, & Y_i^* \ge \mu_1 X_i \end{cases} \tag{5}$$

When the injury severity changes from 0 to 1, it depends on $\mu_1 X_1$. When the injury severity changes from 1 to 2, it depends on $\mu_2 X_2$. The probabilistic model of the ordered logit can be expressed as follows [44]:

$$P(Y_i > j) = \frac{\exp(\alpha + \beta_i X_i)}{1 + \exp(\alpha + \beta_i X_i)} \tag{6}$$

3.3. The Multinomial Logit Model

The multinomial logit model is a widely used method for studying the relationship between independent and dependent variables. This model assumes that the dependent variable is categorical and that the independent variables are linearly related to the log odds of each category. A statistical model that can be used to assess the probability of a crash having a given severity level may be developed with these discrete crash severity levels. The probability of a crash n with a severe outcome i is expressed as follows [45,46]:

$$P_{ni} = P(U_{ni} \ge U_{ni'}), \forall i^{'} \in I, i^{'} \ne i \tag{7}$$

U_{ni} is a function that determines the utility of crash n resulting in severity i. The U_{ni} function can be defined as follows [47]:

$$U_{ni} = \beta_i X_{ni} + \varepsilon_{ni} \tag{8}$$

where X_{ni} is a vector of explanatory variables. β_i represents a vector of estimable coefficients and ε_{ni} is an error term. Assuming that the error term satisfies the independence of

irrelevant alternatives and follows type *I* extreme value distribution, the multinomial logit model can be used to model choice behavior. The model is presented below [48]:

$$P_{ni} = \frac{\exp(\beta_i X_{ni})}{\sum_{i=1}^{I} \exp(\beta_i X_{ni})} \quad (9)$$

3.4. Mixed Logit Model

This study involved implementing the mixed logit model. The MNL model requires the random error term to follow a strict IID assumption, while the mixed logit model relaxes this restriction and allows parameters to vary randomly across individuals. By characterizing individual heterogeneity through the distribution (mean, standard deviation) of model parameters, the mixed logit model can better study heterogeneity. In the logit model formula, the collision occurrence function S_{ni} that determines whether a collision crash i occured can be specified as follows [49]:

$$S_{ni} = \beta_i X_{ni} + \varepsilon_{ni} \quad (10)$$

where X_{ni} is explanatory variables describing the collision crash precursors. β_i represents a vector of the variable coefficients, which are permitted to vary across observations, and ε_{ni} is an error term. The effect of unobserved heterogeneity is considered in the mixed logit model, and the likelihood function can be specified as follows:

$$P_{ni} = \frac{\exp(\beta_i X_{ni})}{\sum_{i=1}^{I} \exp(\beta_i X_{ni})} f(\beta|\varphi) d\varphi \quad (11)$$

where the $f(\beta \mid \varphi)$ is the density function for the random distribution of β and φ is the vector of parameters that define the density function.

3.5. Model Comparison and Marginal Effects

In this paper, the Akaike Information Criterion (*AIC*) and Bayesian Information Criterion (*BIC*) were used to compare the model fitting ability. The *AIC* can be expressed as

$$AIC = 2n - 2\mathrm{In}(L) \quad (12)$$

where L is the maximum value of the likelihood function at convergence, and n is the number of estimated parameters.

The *BIC* can be expressed as

$$BIC = n\mathrm{In}(Q) - 2\mathrm{In}(L) \quad (13)$$

where Q is the number of observations.

The pseudo-R-squared (ρ^2) value is used to evaluate the overall model's fit. The calculation method is as follows:

$$\rho^2 = 1 - LL(\beta)/LL(0) \quad (14)$$

where *LL(β)* is the log-likelihood value at convergence, and *LL(0)* is the log-likelihood value at zero.

4. Estimation Results

Tables 2–4 show the estimation of injury severity by using the generalized ordered logit model, multinomial logit model, and mixed logit model, respectively. A positive coefficient value for an explanatory variable indicates that it is positively connected with the

injury severity level and that increasing its size increases the tendency of the injury severity level. The following presents the estimation results and analysis of the three models.

Table 2. Generalized ordered logit model estimation results.

Variable	Threshold between Light and Medium Injury		Threshold between Medium and Severe Injury	
	Coefficients	*p*-Value	Coefficients	*p*-Value
Constant	0.402 ***	0.056	−2.350 ***	0.000
Crash type				
Sideswipe	−0.395 **	0.013	−1.056 ***	0.000
Rollover	0.965 ***	0.000		
Head-on	−0.295 **	0.042	−0.607 ***	0.009
Vehicle type				
Medium truck			−0.412 *	0.096
Surface condition				
Dry				
Time of day				
Afternoon			0.372 **	0.043
Season				
Winter	0.303 ***	0.008		
Summer				
Slope combination				
Curve	−0.051 *	0.067	−0.087 *	0.057
Slope	0.292 *	0.090	0.590 *	0.078
Curve and slope	1.483 ***	0.000	0.488 **	0.034
Pavement structure				
Dirt and sand	0.581 **	0.016		
Concrete				
Guardrail	0.354 ***	0.004	0.578 ***	0.005
Adjusted ρ^2	0.211			
AIC	3408.792			
BIC	3587.55			

* Indicates significance at the 90% credibility level. ** Indicates significance at the 95% credibility level. *** Indicates significance at the 99% credibility level.

Table 3. Multinomial logit model estimation results.

Variable	Medium Injury		Severe Injury	
	Coefficients	*p*-Value	Coefficients	*p*-Value
Constant	0.201	0.360	−1.359 ***	0.001
Crash type				
Sideswipe			−1.533 ***	0.000
Rollover	1.019 ***	0.000	0.808 **	0.017
Head-on			−0.998 ***	0.000
Vehicle type				
Medium truck			−0.510 **	0.046
Surface condition				
Dry	0.236 **	0.049	−0.387 **	0.044
Time of day				
Morning			−0.597 **	0.012
Season				
Winter	0.356 ***	0.002		
Summer			−0.623 **	0.010
Slope combination				
Curve	−0.032 *	0.074	−0.214 *	0.059
Slope	0.258 *	0.071	0.376 *	0.083
Curve and slope	1.498 ***	0.000	1.591 ***	0.001
Pavement structure				
Dirt and sand	0.545 **	0.027	0.635 *	0.086
Concrete				
Guardrail	0.340 ***	0.006	0.430 **	0.034
Adjusted ρ^2	0.212			
AIC	3390.608			
BIC	3578.262			

The light injury is the base case. * Indicates significance at the 90% credibility level. ** Indicates significance at the 95% credibility level. *** Indicates significance at the 99% credibility level.

Table 4. Mixed logit model estimation results (values in parentheses indicate the standard error of the random parameters).

Variable	Medium Injury		Severe Injury	
	Coefficients	*p*-Value	Coefficients	*p*-Value
Constant	0.112	0.513	−0.692 ***	0.002
Crash type				
Sideswipe			−1.607 (0.375) ***	0.000
Rollover	1.385 (0.984) ***	0.007	0.764 **	0.022
Head-on			−1.016 ***	0.000
Vehicle type				
Medium truck			−0.611 **	0.014
Surface condition				
Dry	0.261 (0.502) ***	0.007		
Time of day				
Morning			−0.616 ***	0.008
Season				
Winter	0.391 ***	0.005		
Summer			−0.649 ***	0.005
Slope combination				
Curve	−0.023 *	0.056	−0.163 *	0.069
Slope	0.182 *	0.076	0.260 *	0.085
Curve and slope	1.654 ***	0.000	1.660 ***	0.001
Pavement structure				
Concrete	−0.274 (0.474) *	0.089	−0.478 *	0.058
Dirt and sand	0.610 (0.751) *	0.095	0.492	0.198
Guardrail	0.240 (0.670) *	0.098		
Adjusted ρ^2	0.287			
AIC	3337.320			
BIC	3503.871			

A light injury is the base case. * Indicates significance at the 90% credibility level. ** Indicates significance at the 95% credibility level. *** Indicates significance at the 99% credibility level.

The performance of the generalized ordered logit model, multinomial logit model, and mixed logit model was measured by the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the pseudo-R-squared (ρ^2) value. The estimation results show that the mixed logit model has the best performance. Moreover, the mixed logit model allows the heterogeneity of variables to be observed. Therefore, this study analyzed the effect of changes in explanatory variables on the probability of injury severity based on the result of the marginal effects for the mixed logit model. The marginal effects for the mixed logit model are shown in Table 5.

The variance inflation factor (VIF) and Pearson correlation test are conducted to check whether there is multicollinearity among the variables. The test result shows that the mean VIF of different types of variables is 1.07 and the Pearson coefficients are below 0.3 or over −0.3, both of which indicate that there is no multicollinearity. The following is an overall evaluation of the three models.

The generalized logit model is under the framework of the traditional ordered logit model. The traditional ordered logit model has proportional assumptions which require the coefficient of the independent variables in the model to be the same in each severity of the dependent variable, thus limiting the influence of the independent variables on different crash injury severity. Table 6 is the test for proportional assumption.

For the proportionality test, the degrees of freedom are 12 and the probability of significance is less than 0.1 statistical significance. The proportionality assumption does not hold for the logit function, and the traditional ordered logit model is invalid. The

generalized ordered logit relaxes the proportionality assumption. The estimation results of the generalized ordered logit model show that 11 variables were significant (0.1 was used in this study).

Table 5. Estimated marginal effects of risk factors in the mixed logit model.

Variable	Marginal Effects		
	light injury	medium injury	severe injury
Crash type			
Sideswipe	0.088 ***	−0.002	−0.086 ***
Rollover	−0.235 ***	0.222 ***	0.012
Head-on	0.061 **	−0.005	−0.055 ***
Vehicle type			
Medium truck	−0.009	0.044	−0.035 **
Surface condition			
Dry	−0.039	0.072 ***	−0.032 ***
Time of day			
Morning	0.007	0.031	−0.038 ***
Season			
Winter	−0.075 ***	0.087 ***	−0.012
Summer	0.013	0.025	−0.039 ***
Slope combination			
Curve	0.012 *	−0.001	−0.012 *
Slope	−0.064	0.050 *	0.013 *
Curve and slope	−0.356 ***	0.312 ***	0.043 *
Pavement structure			
Dirt and sand	−0.131 **	0.111 **	0.019
Concrete	0.042	−0.028	−0.013
Guardrail	−0.082 ***	0.068 **	0.014

A light injury is the base case. * Indicates significance at the 90% credibility level. ** Indicates significance at the 95% credibility level. *** Indicates significance at the 99% credibility level.

Table 6. Test for proportional assumption.

	Chi2	df	P > Chi2
Wolfe Gould	33.41	16	0.007
Brant	30.97	16	0.014
Score	31.64	16	0.011
Likelihood ratio	33.41	16	0.007
Wald	31.16	16	0.013

In the procedure of estimating the multinomial logit model, 13 variables were significant (0.1 was used in this study). For the three crash severity levels, light severity level was used as the base outcome. Because the multinomial requires the assumption that unobserved terms are dependent from one severity level to another, the IIA assumption was checked by a Small and Hsiao test. The test result shows that IIA assumption was not satisfied at the 90% confidence level. More importantly, the multinomial logit model may suffer from unobserved heterogeneity.

5. Discussion

5.1. Crash Characteristics

Regarding the crash characteristics, crash type was found to be the most important factor of injury severity [50–52]. According to the estimation results of the multinomial logit model, the generalized ordered logit model and the mixed logit model, it is found that there are differences in the significant variables identified by the three models. Among them, the multinomial logit model found that the probability of medium- and severe-injury crashes was significantly affected by and negatively correlated with sideswipe crashes and head-on crashes. However, rollover crashes were found to increase the probability

of medium and severe injuries. This can be explained by the fact that trucks have larger volume and mass and there is a risk of falling off cliffs on mountain freeways, which leads to more severe injuries. The results obtained by the other two models, the mixed logit model and generalized ordered logit model, are similar. In the analysis results of the mixed logit model, the random parameter for the rollover variable (Coefficient = 1.385, standard error = 0.984), which uses normal distribution density, was found to increase the chance of medium-injury crashes compared to light-injury crashes. Similarly, the random parameter for the sideswipe variable (coefficient = −1.607, standard error = 0.375) was found to decrease the risk for severe-injury crashes. The generalized ordered logit model suggests similar results.

The marginal effects analysis calculated by the mixed logit model indicated that sideswipe decreases the probability of severe injury by 0.086. Rollover collisions increase the risk of a medium-injury collision by 0.222, and head-on collisions reduce the likelihood of severe harm. The marginal effect on the head-on crashes variable for light injury is significant in the mixed logit model, which is 0.061.

From the estimated results, rollover collision increases the risk of serious injury in heavy truck collisions, which is different from previous research results [53,54]. When a truck approaches a nearby vehicle, the driver will turn the steering wheel sharply to avoid collision with other vehicles, thus causing the truck to roll over. In this case, there is an opportunity to avoid collision with other vehicles and reduce property losses. However, in mountainous freeways, trucks, especially large trucks, have the risk of falling off the cliff when they roll over, resulting in higher-injury crashes.

5.2. Vehicle Characteristics

Due to the great speed difference between trucks and small cars, the possibility of a potential traffic conflict (and therefore collision) may increase. Vehicle type was revealed to be one of the important factors affecting the severity of multi-truck crash injuries [55]. According to the analysis using the multinomial logit model, medium-size truck crashes were found to reduce the risk of severe-injury crashes compared to light-injury crashes. However, this is not significant when compared to medium-injury crashes.

The analysis of the mixed logit model was similar to that of the multinomial logit model. Compared with light-injury crashes, severe-injury crashes are significantly affected by and negatively correlated with the rollover variable. That is, when rollover occurs, the probability of severe-injury crashes will decrease, which means that medium-size trucks reduce the possibility of severe-injury severity.

The reason for this situation may be related to the topography and road geometry of mountain freeways. Compared with light trucks, medium trucks have a larger volume, higher load, and worse braking performance. Therefore, drivers will be more cautious when driving, resulting in the injury severity of medium trucks being higher than that of light trucks. As there are many downhill sections in the mountain expressway, the continuous braking of heavy trucks causes more heat to the brakes, which affects their braking performance and causes more serious injuries. When a medium-size truck is involved in the crash, the possibility for severe injury increases by 0.035.

5.3. Environmental Characteristics

In terms of surface conditions, the impact of dry condition variables on injury severity is significant [16,34]. The result from the multinomial logit model shows that the probability of moderate-injury collision is positively correlated with dry conditions. The estimation results from the mixed logit model are similar to those from the multinomial logit model. The random parameter is the dry condition variable (coefficient = 0.261, standard error = 0.502). Marginal effect research shows that dry conditions increase the probability of medium injury by 0.072.

In terms of the time of day, the estimates obtained by the three models are consistent, indicating that there are differences in the characteristics of multi-truck crashes in different

time periods. According to the analysis by the mixed logit model, it was found that serious-injury collisions were negatively correlated with the morning value and the non-random parameters of the morning variables (Coefficient = −0.616, *p*-value = 0.008); morning crashes can reduce the risk of serious injury by 0.038. This is consistent with previous research results [56,57]. A reasonable reason for the decrease in the probability of serious injury is that the traffic volume is lower in the morning and the visibility is higher.

Regarding the season, the estimation results show that a multi-truck collision in winter is positively related to the severity of the crash, while in summer it is the opposite. The marginal effects calculated by the mixed logit analysis indicated a decrease in the likelihood of severe injury in summer by 0.039. Crashes in winter raise the odds of medium injury by 0.087.

5.4. Roadway Characteristics

Regarding roadway characteristics, the estimation results suggest that the slope variable and curve and slope variable increase injury severity. However, the estimation results show that the curve and slope variable is more significant than the slope variable and the curve variable. The coefficients of the curve and slope variable are 1.654 and 1.660 for both the medium-injury severity and severe-injury severity, respectively. Compared with the coefficients of the curve variable (−0.023) and slope variable (0.182), the high positive coefficients suggest that the curve and slope variable is a more important factor than the curve variable and slope variable. The analysis by the mixed logit model and generalized ordered logit model show findings that are similar to those of the multinomial logit model. According to the marginal effects calculated by the mixed logit model, the analysis shows a decrease in the probability of severe injury for the curve variable by 0.012. Truck crashes occurring on slope sections increase the probability of severe injury by 0.013. The curve and slope variable adds to the probability of severe by 0.31, which determines that curve and slope is a severe factor compared to the others. Most of the studies have only analyzed the vertical and horizontal geometric characteristics separately, such as the curve variable and slope variable. Our study analyzed the combination of horizontal and vertical lines, confirming that the curve and slope variable is a significant factor, which determines that slope combination has an important impact on injury severity.

In terms of pavement structure, the estimation results from the multinomial logit and generalized ordered logit models indicate that dirt and sand variables significantly affect injury severity and the dirt and sand pavement structure is positively correlated with the likelihood of severe injuries. Additionally, in the estimation results of the mixed logit model, in addition to dirt and sand, the concrete variable also significantly affects the medium-injury severity, and the random parameter of the concrete variable (coefficient = −0.274, standard error = 0.474) indicates that the concrete pavement structure can reduce the probability of crash injury severity, which is related to the concrete pavement structure having a higher coefficient of friction than the dirt and sand pavement structure.

For the guardrail variables, the estimated results show that the existence of guardrails on mountain freeways have a negative impact on the severity of injuries, that is, the severity of injuries caused by truck crashes in the sections with guardrails is higher based on light-injury crashes. The random parameter for the rollover variable (coefficient = 0.240, standard error = 0.670) was found to be significant for medium-injury crashes but not significant for severe-injury crashes. According to the marginal effects analyzed by the mixed logit model, the estimation results indicate an increase in the probability of medium- and severe-injury crashes by 0.068 and 0.014, respectively. The reason for this situation is that drivers think driving on a road with guardrails is safe, so they tend to adopt higher speeds and a more aggressive driving style.

6. Conclusions

This study used a multi-truck crash dataset collected in Yunnan Province from 2015 to 2019 on mountain freeways and used the multinomial logit model, generalized ordered

model, and mixed logit model to investigate the risk factors of the injury severity of multi-truck crashes. Our study tested the IIA assumption and multicollinearity of the multinomial logit model. The results show that multicollinearity does not exist, but the IIA assumption is not satisfied. Mixed logit was used to examine the injury severity of truck collisions in order to overcome data with unobserved heterogeneity. The generalized ordered logit model that relaxes the restriction of the proportional odds assumption was also used in our study. The results show that the performance of the mixed logit model was better than those of both the multinomial logit model and generalized ordered logit model. Considering the limitations of topography and road geometry in mountainous regions, there are many combinations of curves and slopes. Therefore, our study focused on the factors contributing to multi-truck crashes on mountain freeways with road geometries, especially on curve–slope combinations. The estimation results indicate that due to the limitations of mountainous terrain, when multi-truck collisions occur on sections of mountainous freeways with a combination of curve and slope, the probability of severe injuries increases due to the large size of trucks and poor visibility on this section of the road.

In terms of the influence of other characteristics on the injury severity of multi-truck crashes, the estimated results indicate that sideswipe, rollover, and head-on collisions have a significant impact on injury severity. Due to the trucks having a high probability of falling off cliffs when turning on their side on mountain freeways, a truck rollover greatly increases injury severity. Therefore, a reminder sign should be added to mountain freeways. Furthermore, the probability of injury severity is decreased since truck drivers are more cautious, drive more slowly, and adopt a prompt deceleration action in the event of a crash on mountain freeways. In terms of environmental characteristics, truck crashes that occur in the morning have a reduced likelihood of severe injuries since there is less traffic and better visibility at that time of day. For road characteristics, dry surface conditions have a significant impact on the severity of truck crashes. Although dry surface conditions (a dirt and sand pavement structure) reduce the probability of light injuries, the probability of medium and severe injuries increases due to drivers relaxing their vigilance in better surface conditions. In addition, the installation of guardrails was found to reduce the probability of medium and severe injuries.

The findings of this study could potentially be used to make policy recommendations for reducing the severity of local road crashes, especially for areas with complex terrain conditions and large freight volumes. For instance, in regard to freeway roadway design, a combination of curve and slope should be avoided if possible, and in-lane rumble strips should be recommended for steep down-slope segments. Moreover, it is recommended that dirt and sand pavement structures be replaced with concrete pavement structures. For traffic management, it is recommended that warning signs to alert drivers to reduce speed in curved road sections be installed due to the limited sight distance in curved road sections. For vehicle design, the structure of large vehicles such as trucks or coaches could be improved to reduce the number of casualties in accidents. Additionally, since large vehicles put significant stress on their tires during braking, it is recommended that they use tires with good heat resistance. By implementing traffic management measures, traffic sustainability can be improved.

In this study, the mixed logit model was developed to analyze the severity of driver injuries in severe multi-truck crashes, so as to understand in depth the causal nature and factors of the severity of driver injuries. These findings are helpful for transportation agencies to determine effective countermeasures to reduce injuries in multi-truck crashes on mountain freeways. However, this article also has some limitations. First, the current research only used a multi-vehicle crash dataset involving trucks. It is strongly recommended that, in the future, the impact of factors on the injury severity between a single-vehicle crash and a multi-vehicle crash should be explored by analyzing the data of single-vehicle crashes involving trucks.

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