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ABSTRACT

Traffic barrier crashes have been a major concern in many prior studies in traffic safety literature, especially in the crash-prone sections of mountainous regions. However, the effect of factors affecting the injury-severities resulting from crashes involving different types of traffic barriers may be different. This paper provides an empirical assessment of the performance of ordered and unordered discrete outcome models for examining the impact of exogenous factors determining the driver injury-severity of crashes involving two types of traffic barriers in mountainous regions: w-beam barriers and cable barriers. For the ordered framework, the alternative modeling approaches include: the generalized ordered logit (GOL) and the random thresholds random parameters generalized ordered logit model (RTRPGOL). Whereas, for the unordered framework, the alternative modeling approaches include: the multinomial logit (MNL), the random parameters multinormal logit (RPL), and the random parameters multinormal logit model with heterogeneity in the means and variances (RPLHMV). Using injury-severity data from 2016 to 2019 for mountainous regions in Guiyang City, China, three injury-severity categories are determined as outcome variables: severe injury (SI), minor injury (MI), and no injury (NI), while the potential influencing factors including drivers-, vehicles-, road-, and environment-specific characteristics are statistically analyzed. The model estimation results show: (a) that the MNL model statistically outperforms the GOL model in terms of goodness-of-fit measures; (b) the RTRPGOL model is statistically superior to the MNL and RPL models; and (c) the RPLHMV model is statistically superior to the RTRPGOL model, and therefore the preferred option among the model alternatives. To that end, the RPLHMV model is leveraged to quantitatively describe the impact of explanatory variables on the driver injury-severity and explore how these factors change over the years (between 2016–2017 and 2018–2019). The results further show that the factors affecting driver injury severities and the effects of significant factors on injury severity probabilities change across traffic barrier crash models and across years. In addition, the results of the temporal effects analysis show that some variables present relative temporal stability, which is important for formulating long-term strategies to enhance traffic safety on mountainous roads. Most importantly, the effects of the explanatory factors that exhibit relative temporal

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stability are found to vary across traffic barrier crashes. For example, trucks, daylight, curved section segments, and high-speed limit (greater than 55 mph) are some of the factors that have opposite effects between traffic barrier crash models. The findings from this paper are expected to help policy makers to take necessary measures in reducing traffic barrier crashes in mountainous regions by forming appropriate strategies, and by allocating properly their available resources at the pre-planning phase.

1. Introduction

Mountainous regions suffer from high crash and fatality rates in countries like the United States, India, and China. In western countries, mountainous highways (e.g., the mountainous section of the I-70 freeway in Colorado, USA) also suffer from high crash rates (Yu et al., 2015), thus revealing a general safety problem in mountainous regions. Single-vehicle crashes are also overrepresented in mountainous regions and are associated with a considerable number of serious injuries and fatal crashes. The National Traffic Safety Administration (NHTSA) in the United States confirms that single-vehicle crashes comprise 60% of all fatal crashes (NHTSA, 2014).

One of the most overlooked types of single-vehicle crashes is related to fixed objects (Amiri et al., 2020). Reports indicate that collisions with fixed objects resulted in 22% of the total fatalities in 2013 in the United States (NHTSA, 2014). Hit-traffic barriers are the common causes of fatalities in the United States (AASHTO, 2011). Therefore, it is clear that in-depth research concerning the occurrence and injury severities of hit-traffic barrier crashes is in need. Fig. 1 depicts the most common types of traffic barrier in mountainous regions in China.

In this regard, there have been considerable efforts to minimize the injury severity of traffic barrier crashes in mountainous regions (e.g., Rezapour et al., 2019a, b; Molan et al., 2019; Molan and Ksaibati 2021a, b; Rezapour et al., 2021). Undoubtedly, their results have provided valuable insights into the contributing factors related to driver-, vehicle-, road-, and environment-specific characteristics associated with crash injury severity. Although traffic barrier types would likely impact the severity of mountainous crashes, prior studies did not present separate performance models for different traffic barrier types – to the best of the authors' knowledge. Differentiating crashes in terms of crash types and investigating differences between crash contributing factors is crucial for identifying specific countermeasures (Intini et al., 2020; Bhowmik et al., 2019a, 2019b, 2021). Consequently, the importance of investigating the differences among crash types should also be highlighted to provide more reliable conclusions by comparing their injury severities and the associated contributing factors. In addition, the prior studies on traffic barrier are mainly based on highway crash data from the USA. Traffic barrier crashes on mountainous roads in other countries are rarely investigated.

In this context, statistics from Guiyang city of China indicate that an overwhelming majority of crashes on mountainous roads involve w-beam barriers and cable barriers. In addition, the effects of factors influencing injury-severities of crashes involving different traffic barrier may change over time, which is also worthy of further investigation. To that end, crash injury-severity data from 2016 to 2019 for mountainous regions in Guiyang City, China, are used. The results from this study can provide a reference for cities with similar mountainous terrains in other regions featuring similar geographical morphologies, driving behaviors, and cultural idiosyncrasies.

The first aim of this paper is to explore the potentially different effects and the possible temporal stability of explanatory factors on traffic barrier crashes. Some explanatory variables may differ over time, may have an opposite effect between traffic barrier crashes, or may have a significant effect in only one type of traffic barrier crash. Such results could potentially be used to help provide new guidelines to reduce the injury-severity of traffic barrier crashes in mountainous regions.

(a)

(b)

Fig. 1. Typical traffic barriers: (a) w-beam barriers; (b) cable barriers.

In addition, the paper provides an empirical comparison of the performance of ordered and unordered discrete outcome models for examining the impact of exogenous factors determining the driver injury-severities of traffic barrier crashes. Evaluation of discrete outcome frameworks for modeling crash injury severity is helpful in choosing a suited way to model traffic barrier crash data.

The rest of the paper is organized as follows: the second section provides a literature review on the injury-severity of traffic barrier crashes in mountainous regions. The third section describes the data used for this study, followed by the fourth section focusing on the methodological approach. The fifth section summarizes the likelihood ratio tests determining the temporal stability of the estimated models. The sixth section presents a detailed discussion of the model estimation results. Finally, the seventh and last section summarizes the findings of this study and discusses potential directions for future research.

2. Literature review

In this section, the existing relevant literature investigating the injury-severity of crashes in mountainous regions is reviewed. First, findings from the studies investigating the factors influencing the crash injury-severity in mountainous areas are summarized. Second, a brief overview of the methodological approaches leveraged in investigating injury-severity of mountainous crashes is presented. Lastly, a brief overview of the current studies investigating traffic barrier crashes injury-severity in mountainous regions is presented.

2.1. Crash injury-severity in mountainous regions: Identified factors

Numerous studies have explored the factors influencing crash injury-severities in mountainous areas (e.g., Yu and Abdel-Aty, 2014a, b; Huang et al., 2018; Rezapour et al., 2019a; Wen and Xue, 2020). The existing studies primarily investigated the driver-, vehicle-, road-, and environment/crash-specific factors affecting the injury-severity outcomes. Hence, the effect of the aforementioned factors on the severity of mountainous crashes is summarized in detail.

Driver-specific characteristics significantly influence the severity of crashes in mountainous regions. In terms of gender, a number of studies have indicated that male drivers are more likely to suffer severe injuries as compared to female drivers (Li et al., 2018; Rezapour et al., 2019a; Yu et al., 2020c); while others concluded that female drivers are less capable of handling and responding to crashes than men, and are prone to more severe injuries (Chen and Chen, 2011; Molan et al., 2020a; Yu et al., 2020c). Behnood and Mannering (2015) found that gender plays a heterogenous role in the severity of road user injuries. With respect to age, older drivers are intuitively found to be more prone to serious injuries (Rezapour et al., 2019b; Islam and Mannering, 2020; Wen and Xue, 2020; Yu et al., 2020a, 2020c). In addition, specific driving behaviors such as speeding, driving under the influence, driving fatigue, and not using a seatbelt are some of the major causes of road traffic crashes and aggravate the degree of the resulting injury-severity (Chen and Chen, 2011, 2013; Rezapour et al., 2019a; Molan et al., 2020a; Wen and Xue, 2020; Yu et al., 2020a, 2020c).

Vehicle-specific factors, including vehicle type and vehicle state (overloading, weaving, or changing lanes), significantly affect the severity of crashes in mountainous regions. Motorcyclists sustain more serious injuries due to being more vulnerable than car or truck drivers (Rezapour et al., 2019a). Compared to passenger cars, crashes involving trucks are more likely to cause severe and fatal injuries in mountainous regions resulting from brake failure or loss of control on downhill sections (Rezapour et al., 2019a). On the contrary, Yu and Abdel-Aty (2014b) concluded that passenger cars are more prone to severe crashes than trucks, especially during the daytime. Furthermore, the vehicle's state, such as overloading, weaving, or changing lanes, is found to increase the risk of severe crashes in mountainous regions (Chen et al., 2015; Rezapour et al., 2019a; Wang and Prato, 2019).

Several road-specific characteristics (e.g., topography, road geometry, speed limit, road surface conditions, Average Annual Daily Traffic - AADT, section type, type of roadside barriers) significantly affect the severity of crashes in mountainous areas. Findings from the previous studies indicate that the slope of the roadway and the presence of curves significantly affect the injury-severity of crashes in mountainous regions (Chen and Chen, 2011; Yu and Abdel-Aty, 2014a, b; Huang et al., 2018; Li et al., 2018; Wang and Prato, 2019; Haq et al., 2020a, 2020b). Higher speed limits in mountainous regions are also found to be more dangerous for drivers (Chen and Chen, 2013; Rezapour et al., 2019a, b; Molan et al., 2020a; Rezapour et al., 2020; Wen and Xue, 2020). For example, Rezapour et al., (2019a) found that for a one-unit increase in the posted speed limit above 55 mph on downgrades, the risk of crash-injury severity would increase by 2.3 times. Furthermore, dry road surfaces in mountainous regions are associated with severe injuries (Huang et al., 2018; Rezapour et al., 2019a; Molan et al., 2020a; Rezapour et al., 2020). Huang et al. (2018) indicated that drivers drove more carefully in adverse weather conditions than in dry road conditions, based on crash data from Hunan Province, China. In addition, increases in the traffic flow are associated with an aggravated risk of crash occurrence. Wen and Xue (2020) also reported that the risk of serious injuries is most significant on 'special' road sections, such as sharp turns, long continuous slopes, and tunnels.

Environment-and crash-specific characteristics (e.g., weather conditions, lighting conditions, time of day, and crash type) significantly influence the severity of crashes. First, adverse weather conditions such as rain, snow, fog, and wind, pose a greater risk of severe or fatal injuries as compared to clear weather conditions (Chen and Chen, 2011; Duddu et al., 2018; Li et al., 2018; Wang and Prato, 2019; Wen and Xue, 2020). Second, nighttime crashes are more likely to result in more severe injury as compared to daytime crashes (Duddu et al., 2018; Huang et al., 2018; Li et al., 2018; Wang and Prato, 2019; Wen and Xue, 2020; Yu et al., 2020a). However, Rezapour et al. (2019a) found that the likelihood of a severe injury during dark conditions decreases by 54.8% as compared to daylight conditions. In addition, Yu and Abdel-Aty (2014b) and Haq et al. (2020b) reported that the frequency of severe crashes is higher during the day. Lastly, several studies have shown that single-vehicle rollover crashes on mountainous highways are prone to more severe injuries (Chen and Chen, 2011, 2013; Rezapour et al., 2019b; Haq et al., 2020a, b; Molan et al., 2020a; Wen and Xue, 2020).

2.2. Crash injury-severity in mountainous regions: Methodological approaches

Traditional logit and probit models have been widely used to investigate the factors affecting the injury-severity of mountainous crashes. However, traditional models assume that the estimated parameters are fixed for all observations, which may lead to biased parameter estimates and erroneous inferences (Mannering et al., 2016). Moreover, traditional crash databases often lack relevant information that may affect crash injury-severity, which in turn may result in unobserved heterogeneity. To effectively account for unobserved heterogeneity, advanced econometric modeling frameworks are utilized in recent studies. In addition, machine learning models are also utilized in the literature to gain better predictive performance. The relevant studies that investigated crashes in mountainous regions are listed in Table 1, along with the study locations, methodological approaches, and summarized findings. It is observed that the random parameters logit model (Yu and Abdel-Aty, 2014a, 2014b; Rezapour et al., 2019b), hierarchical Bayesian models (Chen et al., 2015; Haq et al., 2020a), classification and regression tree model (Huang et al., 2018) are popularly leveraged in these studies.

The random parameters approach in the aforementioned studies assumed that the distribution of random parameters was independent (Mannering et al., 2016; Behnood and Mannering, 2017b; Hou et al., 2019), and the possibility of explanatory factors affecting the individual parameter estimates have not been accounted for. To address this issue, a random parameters with heterogeneity in means and variances (RPLHMV) approach is leveraged in the literature, which is capable of capturing multilayered unobserved heterogeneity (Islam and Mannering, 2020).

This new approach has been used by traffic safety analysts to investigate injury-severities of work zone rear-end collisions (Islam et al., 2020; Yu et al., 2020b), bicyclist/motorcyclist injury-severities (Behnood and Mannering, 2017a; Alnawmasi and Mannering, 2019; Waseem et al., 2019), and crash injury-severities on highways (Behnood and Mannering, 2019; Islam and Mannering, 2020). However, the application of this approach in the analysis of crashes in mountainous regions appears to be rather limited. It should be noted that the severity of crashes on mountainous roads is more complex (in other words, more heterogenous) than in non-mountainous counterparts (Wen and Xue, 2020).

2.3. Traffic barrier crashes injury-severity in mountainous regions

Traffic barriers significantly reduce the risk of severe and fatal injuries if the crash occurs unavoidable (Rezapour et al., 2019a, 2019b; Molan et al., 2019; Molan et al., 2020a, b, c, d; Molan and Ksaibati 2021a, b; Rezapour et al., 2021). In recent years, several studies have explored the relationship between traffic barrier and the severity of crashes (i.e., Hu and Donnell, 2010; Russo and Savolainen, 2018; Molan et al., 2019; Rezapour et al., 2019b; Molan et al., 2020a; Park et al. (2016)). A summary of earlier research on driver injury severities involving traffic barrier crashes from the perspective of the various ordered and unordered discrete outcome models is provided in Table 2. For example, Molan et al. (2020a) employed ordered logit models to investigate the severity of crashes considering the presence of three roadside barriers (guardrail, rigid, and cable barriers). Zou et al. (2014) demonstrated that road barriers (guardrails, cable barriers, and concrete barriers) decreased injury-severity compared to other roadside objects on Indiana highways using mixed-effects binary logistic model. Rezapour et al. (2019b) found that barrier height and offset distance significantly impacted the crash injury-severity on two-lane roads in Wyoming based on the mixed logit model. Hosseinpour and Haleem (2021) used mixed logit models to investigate the impacts of barrier-specific characteristics on crash injury-severity involving high-tension flexible barriers and strong-post guardrails on interstate highways in Alabama. Table 2 shows that only a few studies provide any type of comparison for

Table 1
Summary of methodological approaches of relevant studies investigating crashes in mountainous regions.

Authors	Study location	Methodological approach	Identified factors
Yu and Abdel-Aty (2014a)	Colorado, USA	Correlated random parameter logit model	Large variations of speed or low temperature during snow seasons
Yu and Abdel-Aty (2014b)	Colorado, USA	Hierarchical Bayesian binary probit models	Large variations of speed during snow seasons
Chen et al., (2015)	New Mexico, USA	Hierarchical Bayesian random intercept model	Wet road and disabled vehicle damage
Rezapour et al., (2019b)	Wyoming, USA	A mixed binary logistic regression model	Traffic barrier height, traffic barrier offset, and shoulder-width
Haq et al., (2020a)	Wyoming, USA	Bayesian binary logit approach	Fire or rollover, guardrail hits, speeding, and curved segments
Huang et al., (2018)	Hunan, China	A classification and regression tree model	Speeding during the afternoon or evening

Table 2
Summary of the ordered and unordered discrete outcome models for injury severities of traffic barrier crashes.

Methodological Approach		Previous Research
Ordered discrete outcome framework	Ordered logistic models	Rezapour et al., 2019a; Molan et al., 2020a, 2020d; Rezapour et al., 2021
	Random parameters ordered logit models	Molan et al., 2019; Molan et al., 2020b, 2020c; Molan and Ksaibati 2021a, 2021b; Russo and Savolainen, 2018
Unordered discrete outcome framework	Mixed logit models	Rezapour et al., 2019b; Russo and Savolainen, 2018; Hosseinpour and Haleem, 2021
	Nested logit models	Hu and Donnell, 2010
	Mixed-effects binary logit models	Zou et al., 2014

the performance of ordered and unordered discrete outcome models for examining the impact of exogenous factors on driver injury severity of traffic barrier crashes.

In addition, recent studies have not developed separate performance models for different traffic barrier types. Differentiating crashes in terms of crash types and studying differences between crash contributing factors is thus crucial for identifying specific countermeasures (Intini et al., 2020; Bhowmik et al., 2019a, 2019b, 2021). Consequently, besides the mixed analysis of hit-traffic barrier crashes, the importance of using the same dataset to investigate the differences among crash types should also be highlighted to provide more reliable inferences by comparing their injury severities and the associated contributing factors at the same spatiotemporal level. Note that Molan et al. (2020a) employed ordered logit models to investigate the severity of crashes considering the presence of three roadside barriers (guardrail, rigid, and cable barriers). However, traditional logit and probit models assume that the estimated parameters are fixed for all observations, which may lead to biased parameter estimates and erroneous inferences (Eluru et al., 2008; Mannering et al., 2016). Furthermore, the current research on traffic barrier crashes rarely accommodates the potential temporal effects of the influencing factors. Meanwhile, these studies are mainly based on highway crash data from the USA. Traffic barrier crashes on mountainous roads in other countries are rarely investigated. Since substantial differences exist in driving behavior, barrier selection/usage, crash characteristics, and influencing factors across different countries and between mountainous and non-mountainous roads, it is important to investigate country- and region-specific crashes for localized insights.

Using traffic barrier crash injury-severity data from 2016 to 2019 for mountainous regions in Guiyang City, China, this paper provides an empirical assessment of the performance of ordered and unordered discrete outcome models for examining the impact of exogenous factors on driver injury severity. To that end, a gamut of ordered (GOL and RTRPGOL) and unordered (MNL, RPL and RPLHMV) discrete outcome models are estimated.

3. Data description

Guiyang city is located in southwestern China and has become a highly crash-prone location due to special geographical conditions, with mountainous areas accounting for more than half of the city (Liu et al., 2010). This makes Guiyang city a good candidate location to investigate to understand better the factors affecting driver injury-severities due to crashes in mountainous regions.

For the analysis, four-year (2016–2019) data are used from traffic barrier crashes that occurred in Guiyang, China. The data were collected by the Guiyang Public Security Traffic Administration Bureau. Following the official dataset reports, the injury severity outcomes are categorized as follows: no injury, minor injury, and severe injury. The dataset consists of 3,045 traffic barrier crashes in mountainous areas: 1,556 crashes involving w-beam barrier and 1,489 crashes involving cable barrier. It should be noted that this study also intends to explore the temporal stability of injury severity models for traffic barrier crashes. To that end, the dataset is split into two subsets, one for years 2016–17, and one for years 2018–19. Fig. 2 display the frequency distribution of the crash injury severity categories (66.97%, 17.67%, and 15.36% for no injury, minor injury, and severe injury in w-beam barrier crashes, respectively; and 65.08%, 26.39%, and 8.53% for no injury, minor injury, and severe injury in cable barrier crashes, respectively). Apart from the injury severity outcomes, the crash dataset covers crash-related information, including driver-specific characteristics (age, gender, driving experience, driver under alcohol influence, seatbelt use), vehicle-specific characteristics (vehicle type, vehicle state), road-specific characteristics (grade, section type), environment-specific characteristics (weather conditions, lighting conditions), and temporal characteristics (day and time of the crash). Table 3 presents the descriptive statistics of explanatory variables used in the injury-severity models.

4. Methodology

This section provides a brief description of the methodology of all models considered for investigating driver injury severities.

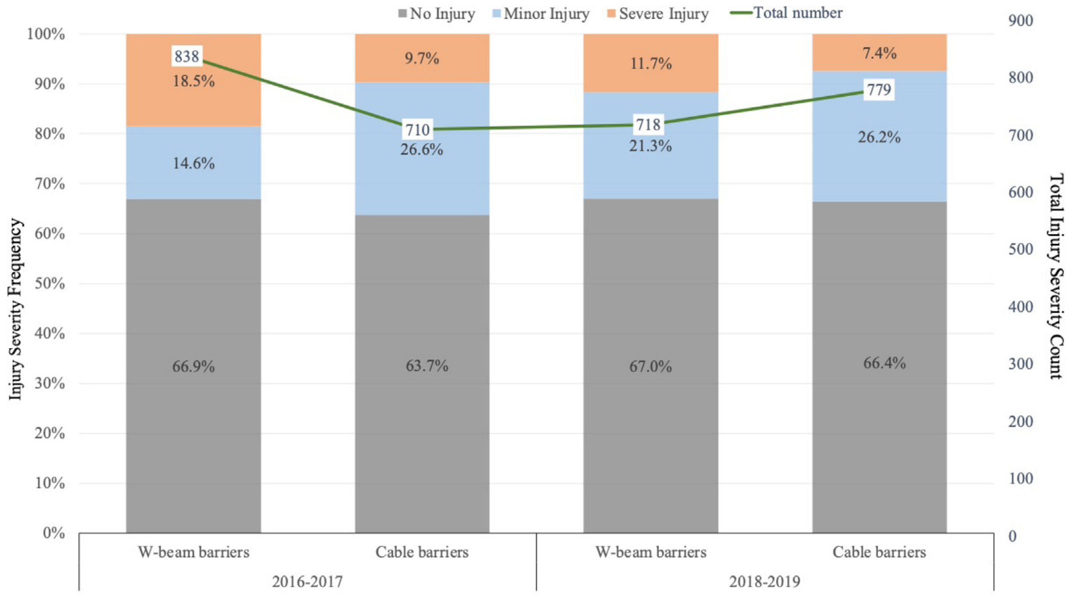

Fig. 2. Frequency distribution of the crash injury severity categories.

4.1. Generalized ordered logit model

In the traditional ordered discrete outcome model (i.e., OL), the discrete injury severity levels (y_i) are assumed to be associated with an underlying continuous latent variable (y_i^*). This latent variable is typically specified as the following linear function (Yasmin and Eluru, 2013; Eluru, 2013; Yasmin et al., 2015; Bhowmik et al., 2019a, 2019b; Washington et al., 2020):

$$y_i^* = X_i\beta + \varepsilon_i,\ y_i = j,\ \text{if}\ \mu_{j-1} < y_i^* < \mu_j,\ \text{for}\ i = 1,\ 2,\ \cdots,\ N; j = 1, 2, \cdots, J \tag{1}$$

where, i ($i = 1, 2, \cdots, N$) represents the drivers, X_i is a vector of exogenous variables (excluding the constant), μ represents the thresholds associated with these severity levels, β is a vector of unknown parameters to be estimated, j are the integer ordered injury-severity levels, and ε is the random disturbance term that is assumed to follow a standard logistic distribution.

The generalized ordered logit model (i.e., GOL model) relaxes the constant threshold across population restriction to provide a flexible form of the traditional OL model. The basic idea of the GOL is to represent the threshold parameters as a linear function of a set of explanatory parameters (Eluru et al., 2008; Fountas and Anastasopoulos, 2017). Thus, the GOL modeling scheme is expressed as:

$$\mu_{i,j} = \mu_{i,j-1} + \exp(t_j + d_j S_i \tag{2}$$

where, t is the intercept for each threshold, S are vectors of variables affecting the thresholds, and d are vectors of estimable parameters for S.

4.2. Random thresholds random parameters generalized ordered logit model

The random thresholds random parameters generalized ordered logit model (i.e., RTRPGOL) extends the GOL model by allowing for unobserved heterogeneity in the parameters and the thresholds.

To allow the thresholds to concurrently vary across the observations, Eq. (2) can be re-written as (Fountas and Anastasopoulos, 2017):

$$\mu_{i,j} = \mu_{i,j-1} + \exp(t_j + \gamma_j \mu_{ij} + d_j S_i \tag{3}$$

where, μ_{ij} is a normally distributed term with mean zero and standard deviation one, while t_j and γ_j are the mean and standard deviation of the threshold intercept term, respectively.

To simultaneously account for unobserved heterogeneity in the outcome probability process, the effect of the explanatory parameters can be allowed to vary across the observations. This can be accomplished through the use of random parameters, in which case the estimable parameters become (Washington et al., 2020):

$$\beta_i = \beta + \Gamma w_i \tag{4}$$

Table 3
Descriptive statistics of explanatory variables.

Variables	2016–2017				2018–2019			
	W-beam		Cable		W-beam		Cable	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Driver characteristics								
Male indicator (1 if male driver, 0 otherwise)	0.916	0.277	0.907	0.291	0.919	0.273	0.909	0.288
Female indicator (1 if female driver, 0 otherwise)	0.084	0.277	0.093	0.291	0.081	0.273	0.091	0.288
Middle age driver indicator (1 if driver age between 31 and 60 years, 0 otherwise)	0.891	0.311	0.889	0.315	0.866	0.341	0.865	0.342
Young driver indicator (1 if driver age below 30, 0 otherwise)	0.109	0.311	0.111	0.315	0.134	0.341	0.135	0.342
Intermediate driving experience indicator (1 if driving experience between 10 and 15 years, 0 otherwise)	0.202	0.401	0.199	0.399	0.166	0.372	0.146	0.354
Novice driving experience indicator (1 if driving experience between 3 and 10 years, 0 otherwise)	0.495	0.500	0.531	0.499	0.545	0.498	0.579	0.494
Rookie driving experience indicator (1 if driving experience below 3 years, 0 otherwise)	0.128	0.334	0.132	0.339	0.111	0.315	0.107	0.309
Expert driving experience indicator (1 if driving experience above 15 years, 0 otherwise)	0.175	0.381	0.138	0.345	0.178	0.383	0.168	0.374
No driver seatbelt use indicator (1 if driver without seatbelt, 0 otherwise)	0.150	0.358	0.108	0.311	0.127	0.333	0.107	0.309
Driver seatbelt use indicator (1 if driver with seatbelt, 0 otherwise)	0.850	0.358	0.892	0.311	0.873	0.333	0.893	0.309
Driver under alcohol influence indicator (1 if driver under alcohol influence, 0 otherwise)	0.154	0.361	0.162	0.369	0.188	0.391	0.173	0.379
Vehicle characteristics								
Car indicator (1 if car, 0 otherwise)	0.741	0.438	0.858	0.350	0.783	0.413	0.849	0.359
Truck indicator (1 if truck, 0 otherwise)	0.259	0.438	0.142	0.350	0.217	0.413	0.151	0.359
Improper braking and steering indicator (1 if improper breaking and steering, 0 otherwise)	0.442	0.497	0.462	0.499	0.408	0.492	0.334	0.472
Improper lane changing indicator (1 if improper lane changing, 0 otherwise)	0.104	0.305	0.134	0.341	0.187	0.390	0.221	0.415
Non local vehicle indicator (1 if non-local vehicles, 0 otherwise)	0.135	0.342	0.079	0.270	0.128	0.334	0.092	0.290
Local vehicle indicator (1 if local vehicles, 0 otherwise)	0.865	0.342	0.921	0.270	0.872	0.334	0.908	0.290
Roadway characteristics								
Curved section indicator (1 if curved section segment, 0 otherwise)	0.316	0.465	0.669	0.471	0.352	0.478	0.669	0.471
Straight sections indicator (1 if straight sections, 0 otherwise)	0.684	0.465	0.331	0.471	0.648	0.478	0.331	0.471
Road in good condition indicator (1 if road with good condition, 0 otherwise)	0.969	0.173	0.966	0.181	0.965	0.183	0.981	0.138
Road in bad condition indicator (1 if road with bad condition, 0 otherwise)	0.031	0.173	0.034	0.181	0.035	0.183	0.019	0.138
Dry surface indicator (1 if road surface condition was dry, 0 otherwise)	0.723	0.448	0.779	0.415	0.724	0.447	0.718	0.450
Wet surface indicator (1 if road surface condition was wet, 0 otherwise)	0.277	0.448	0.221	0.415	0.276	0.447	0.282	0.450
Speed limit indicator (1 if speed limit > 55 mph, 0 otherwise)	0.301	0.459	0.242	0.429	0.217	0.413	0.272	0.445
Intersection indicator (1 if crash occurred in intersection, 0 otherwise)	0.155	0.362	0.200	0.400	0.171	0.377	0.167	0.373
Ramp indicator (1 if crash occurred in ramp, 0 otherwise)	0.041	0.197	0.008	0.092	0.091	0.287	0.035	0.183
Homogeneous section indicator (1 if crash occurred in a homogeneous section, 0 otherwise)	0.678	0.468	0.751	0.433	0.063	0.243	0.013	0.113
Tunnel indicator (1 if crash occurred in tunnel, 0 otherwise)	0.126	0.333	0.041	0.198	0.675	0.469	0.786	0.411
Small uphill grade indicator (1 if 0–2% vertical grade, 0 otherwise)	0.758	0.429	0.748	0.435	0.758	0.429	0.783	0.412
Small downhill grade indicator (1 if −2–0% vertical grade, 0 otherwise)	0.082	0.275	0.169	0.375	0.092	0.289	0.123	0.329
Large uphill grade indicator (1 if 2% or greater vertical grade, 0 otherwise)	0.062	0.241	0.042	0.201	0.049	0.215	0.056	0.231
Large downhill grade indicator (1 if −2% or less vertical grade, 0 otherwise)	0.098	0.297	0.041	0.198	0.102	0.302	0.037	0.189
Environment characteristics								
Winter indicator (1 if winter, 0 otherwise)	0.254	0.436	0.193	0.395	0.223	0.416	0.232	0.423
Summer indicator (1 if summer, 0 otherwise)	0.267	0.443	0.270	0.444	0.256	0.437	0.266	0.442
Spring indicator (1 if spring, 0 otherwise)	0.199	0.400	0.220	0.414	0.291	0.455	0.268	0.443
Autumn indicator (1 if autumn, 0 otherwise)	0.279	0.449	0.317	0.466	0.230	0.421	0.234	0.423
Sunny indicator (1 if sunny, 0 otherwise)	0.278	0.448	0.308	0.462	0.292	0.455	0.279	0.449
Cloudy indicator (1 if cloudy, 0 otherwise)	0.527	0.500	0.546	0.498	0.542	0.499	0.542	0.499
Rainy/snowy/foggy indicator (1 if rainy/snowy/foggy, 0 otherwise)	0.195	0.396	0.145	0.352	0.166	0.372	0.180	0.384
Low visibility indicator (1 if visibility below 50 m, 0 otherwise)	0.107	0.310	0.118	0.323	0.110	0.313	0.090	0.286
Medium-low visibility indicator (1 if visibility between 50 and 100 m, 0 otherwise)	0.321	0.467	0.386	0.487	0.306	0.461	0.336	0.473
Medium visibility indicator (1 if visibility between 100 and 200 m, 0 otherwise)	0.331	0.471	0.321	0.467	0.247	0.431	0.294	0.456
High visibility indicator (1 if visibility above 200 m, 0 otherwise)	0.241	0.428	0.175	0.380	0.337	0.473	0.280	0.449
Daylight indicator (1 if daylight, 0 otherwise)	0.443	0.497	0.468	0.499	0.486	0.500	0.498	0.500
Dark lighted indicator (1 if dark lighted, 0 otherwise)	0.352	0.478	0.380	0.486	0.312	0.464	0.358	0.480
Dark-no light indicator (1 if dark without streetlights, 0 otherwise)	0.205	0.404	0.152	0.359	0.202	0.402	0.144	0.351
Weekends indicator (1 if crash occurred during the weekends, 0 otherwise)	0.716	0.451	0.749	0.434	0.701	0.458	0.678	0.468
Weekdays indicator (1 if crash occurred during the weekdays, 0 otherwise)	0.284	0.451	0.251	0.434	0.299	0.458	0.322	0.468
Morning peak indicator (1 if time 7:00–8:59, 0 otherwise)	0.240	0.427	0.206	0.404	0.255	0.436	0.208	0.406
Nighttime off-peak indicator (1 if time 19:30–23:59, 0 otherwise)	0.169	0.375	0.128	0.335	0.138	0.345	0.130	0.336
Early morning indicator (1 if time 00:00–7:00, 0 otherwise)	0.086	0.280	0.120	0.325	0.127	0.333	0.168	0.374
Afternoon peak indicator (1 if time 17:00–19:29, 0 otherwise)	0.344	0.475	0.341	0.474	0.276	0.447	0.295	0.456
Daytime off-peak indicator (1 if time 9:00–16:59, 0 otherwise)	0.161	0.368	0.206	0.404	0.205	0.404	0.199	0.399

where, β is the mean of the random parameters' vectors, Γ is the diagonal matrix of standard deviations, and w_i is a normally distributed term with mean zero and variance one. To improve estimation efficiency, a simulated maximum likelihood estimation process is employed using a Halton sequence approach, in order to draw random values of β from the parameter density function $q(\beta|\varphi)$, where φ denotes a vector of parameters of the density distribution (e.g., mean and standard deviation, in the case of the normal distribution).

In this context, the ordered probability of each different severity level j for each crash observation, can be calculated as (following the formulation of Washington et al., 2020):

$$P(y=j) = \Phi(\mu_j - \beta_i X_i)\Phi(\mu_{j+1} - \beta_i X_i) \tag{5}$$

where, $P(y=j)$ is the probability of the injury-severity level j, Φ represents the cumulative function of the standard normal distribution, μ denotes the marginal thresholds for outcome j, and all the other terms are as previously defined.

4.3. Multinomial logit model

Let us consider the probability of a driver i suffering a specific injury-severity level j. The alternative specific latent variables for the multinomial logit model (i.e., MNL) take the form of:

$$U_{ij} = \beta_j X_{ij} + \varepsilon_{ij} \tag{6}$$

where, β_j is a vector of coefficients to be estimated for outcome j, X_{ij} is a vector of exogenous variables, U_{ij} is a function of covariates determining the injury-severity outcome, and ε_{ij} is the random component assumed to follow a Gumbel distribution. Thus, the MNL probability expression is as follows (Washington et al., 2020; Ahmed et al., 2021a, 2021b):

$$P_i(j) = \frac{\exp[\beta_j X_{ij}]}{\sum_{j=1}^{J} \exp[\beta_j X_{ij}]} \tag{7}$$

4.4. Random parameters logit models with heterogeneity in means and variances

Lastly, to account for the multilayered unobserved heterogeneity of the crash data in terms of (a) factors varying across the observations; (b) factors affecting the mean of the parameter density function of the random parameters (and thus shifts in the peak of the distribution of the betas); and (c) factors affecting the variance of the parameter density function of the random parameters (and thus changes in the tails of the distribution of the betas). The random parameters logit models with heterogeneity in means and variances (RPLHMV) are estimated to identify factors influencing the driver injury-severity are introduced (Mannering et al., 2016; Eker et al., 2019; Ahmed et al., 2020; Ahmed et al., 2021c; Pantangi et al., 2021):

$$\beta_{ij} = \mathrm{\beta_j} + \boldsymbol{\Theta}_{\mathbf{ij}}\mathbf{Z}_{\mathbf{ij}} + \sigma_{ij} EXP\left(\psi_{\mathbf{ij}}\mathbf{W}_{\mathbf{ij}}\right) + \upsilon_{ij} \tag{8}$$

where, $\mathrm{\beta_j}$ is the mean parameter estimate across all drivers, $\mathbf{Z}_{\mathbf{ij}}$ are vectors of explanatory variables that influence the mean, $\boldsymbol{\Theta}_{\mathbf{ij}}$ are vectors of corresponding estimable parameters, $\mathbf{W}_{\mathbf{ij}}$ are vectors of explanatory variables that capture heterogeneity in variances, σ_{ij}, $\psi_{\mathbf{ij}}$ is a vector of corresponding estimable parameters, and υ_{in} is a disturbance term. Then, the outcome probability of the RPLHMV model formulation can be expressed as (Washington et al., 2020):

$$P_i(j|\varphi) = \int \frac{\exp\left(\beta_{\mathbf{j}}\mathbf{X}_{\mathbf{ij}}\right)}{\sum_{i\in I} \exp\left(\beta_{\mathbf{j}}\mathbf{X}_{\mathbf{ij}}\right)} f(\beta_{\mathbf{j}}|\varphi) d\beta_{\mathbf{j}} \tag{9}$$

where, $p_i(j|\varphi)$ is the probability of injury severity level j conditional on $f(\beta_{\mathbf{j}}|\varphi)$, and $f(\beta_{\mathbf{j}}|\varphi)$ is the density function of $\mathrm{\beta_j}$ With φ refers to a vector of parameters (means and variances).

The RPLHMV model is estimated with a simulated maximum likelihood method, and 1,000 Halton draws are used to achieve stable parameter estimates (McFadden and Train, 2000). In terms of the distribution of the random parameters, the normal distribution is used to achieve the best goodness-of-fit (Anastasopoulos and Mannering, 2011; Behnood and Mannering, 2017a, b; Fountas and Anastasopoulos, 2017; Fountas et al., 2018).

Pseudo-elasticities are computed to quantitatively describe the impact of explanatory variables on the driver injury-severity. In this paper, all variables used in the estimated models are binary indicator variables. Therefore, the pseudo-elasticities quantify the change in outcome probability when an explanatory variable changes from "0" to "1" (Washington et al., 2020).

5. Likelihood ratio tests for temporal and parameter transferability

We conducted chi-square distributed likelihood ratio tests to determine whether there is any difference between injury-severity outcomes for each traffic barrier type and whether these differences change over time. To begin, for each time period (2016–2017 and 2018–2019), likelihood ratio tests were conducted to compare injury-severity outcomes for each traffic barrier type. The test statistic is (Washington et al., 2020):

$$\chi_t^2 = -2[LL(\beta_{combined,t}) - LL(\beta_{w-beam,t}) - LL(\beta_{cable,t})] \tag{10}$$

where, $LL(\beta_{combined,t})$ is the log-likelihood at the convergence of the model using all of the available traffic barrier crashes data in the year t (either year 2016–2017, or 2018–2019), $LL(\beta_{w-beam,t})$ is the log-likelihood at the convergence of the model using w-beam barriers data only in year t, $LL(\beta_{cable,t})$ is the log-likelihood at convergence using cable barriers data only in year t. The test results (see Table 4) show that the null hypotheses that the identified factors between different time periods are the same can be rejected with over 99.99% confidence.

Next, the temporal stability of injury-severity outcomes for each traffic barrier type is tested. The test statistic is (Washington et al., 2020):

$$\chi^2_{barriers} = -2[LL(\beta_{2016-2019,barriers}) - LL(\beta_{2016-2017,barriers}) \\ -LL(\beta_{2018-2019,barriers})] \tag{11}$$

where, $LL(\beta_{2016-2019,barriers})$ is the log-likelihood at convergence using 2016–2019 time period data, $LL(\beta_{2016-2017,barriers})$ is the log-likelihood at convergence using only 2016–2017 time period data, and $LL(\beta_{2018-2019,barriers})$ is the log-likelihood at convergence using only 2018–2019 time period data. It also can be concluded that the null hypotheses that the identified factors among the two traffic barriers are the same can be rejected with over 99.99% confidence. In other words, statistically significant temporal instability exists among the two traffic barriers.

To further test the temporal instability of the estimated parameters between any two of the time periods involving the two different types of traffic barrier (w-beam barriers and cable barriers), we used the following alteration of the likelihood ratio test (Mannering, 2018; Washington et al., 2020; Hou et al., 2022):

$$\chi^2_{t,t'} = -2[LL(\beta_{t,t'}) - LL(\beta_t)] \tag{12}$$

where, $LL(\beta_{t,t'})$ is the log-likelihood at the convergence of the model using the converged parameters from the t time period of data on the t' the time period of data, and $LL(\beta_t)$ is the log-likelihood at the convergence of the model using the t time period of data. The results of these tests (see Tables 5.1–5.3) are consistent with the transferability tests presented in Tables 4-5.1 and show that the null hypothesis that the identified factors among the two traffic barriers are the same across the same time periods can be rejected. The combination of the likelihood ratio tests in Tables 4 through 5.3 provides strong evidence that separate models are warranted by the study period.

6. Model estimation results

6.1. Empirical assessment of ordered and unordered discrete outcome modeling frameworks

The issue of selecting between multinomial logit and generalized ordered logit models has been discussed in Balusu et al. (2018). It is shown that the mixed generalized ordered models have significant issues in applications to safety (e.g., threshold variance problem). Also, mixed generalized ordered models are sometimes argued to be parsimonious; however, this is usually associated with specification errors (e.g., omitted variables or restrictive functional form).

To further explore the two frameworks, we provide an empirical assessment of the performance of the ordered and unordered discrete outcome models for examining the impact of exogenous factors determining the driver injury-severity of traffic barrier crashes in mountainous regions. Therefore, we estimate six model alternatives: (1) GOL, (2) RTRPGOL, (3) MNL, (4) RPL, (5) RPLHM, and (6) RPLHMV model. To test the performance of the ordered and unordered models, we compute the Akaike Information Criterion (AIC) and the corrected (for the number of parameters) AIC - AICc, the Bayesian Information Criteria (BIC), and the R-Squared and adjusted R-Squared. Smaller AICs values, and higher adjusted R-Squared values indicate a better model fit (Washington et al., 2020). The goodness-of-fit measures for the estimated models are presented in Table 6.[1] As can be seen from the table, the results are consistent across goodness-of-fit measures (AIC/AICs/BIC) for the estimated models.

Table 6 provides some interesting findings: (a) the RTRPGOL model is statistically superior to the GOL model for the ordered framework; (b) the RPLHMV model provides a superior statistical fit as compared to its other two logit model counterparts for the unordered framework; (c) the MNL model statistically outperforms (even though marginally) the GOL model; (d) the RTRPGOL model is statistically superior to the MNL and RPL models (except for the 2016–2017 w-beam barriers model); and (e) the RPLHMV is statistically superior to the RTRPGOL model (across all models and goodness-of-fit measures).

[1] In addition to the aforementioned goodness-of-fit measures, a series of likelihood ratio tests (Washington et al, 2020) were conducted between the two ordered models (testing the statistical superiority between the GOL and the RTRPGOL models), and among the three unordered models (testing the statistical superiority between the following model pairs: MNL and RPL, RPL and RPLHMV, and MNL and RPLHMV). The test is $\chi^2 = -2[LL(\beta_{modelA}) - LL(\beta_{modelB})]$, where $LL(\beta_{model\ A})$ and $LL(\beta_{model\ B})$ are the log-likelihoods at convergence of the competing models A and B, respectively. The test is chi-squared distributed, and has degrees of freedom equal to the difference in the number of parameters between the two models. The test results were consistent with the finding of the goodness-of-fit measures, in that the RTRPGOL statistically outperforms its GOL modeling counterpart at a 0.99 level of confidence, and that the RPLHMV is statistically superior to its MNL and RPL modeling counterparts also at the 0.99 level of confidence.

Table 4
The χ^2 values for different time periods (degrees of freedom in parentheses and confidence level in brackets).

$\chi^2_{2016-2017}$	$\chi^2_{2018-2019}$
164.851 (17) [99.99%]	225.537 (19) [99.99%]

Table 5.1
The χ^2 values for different types of traffic barrier (degrees of freedom in parentheses and confidence level in brackets).

χ^2_{w-beam}	χ^2_{cable}
85.53 (19) [99.99%]	95.006 (20) [99.99%]

Table 5.2
The χ^2 values for different time periods for the w-beam barrier model (degrees of freedom in parentheses and confidence level in brackets).

	2016–2017	2018–2019
2016–2017	–	23.442 (19) [76.45%]
2018–2019	58.135 (16) [99.99%]	–

Table 5.3
The χ^2 values for different time periods for the cable barrier model (degrees of freedom in parentheses and confidence level in brackets).

	2016–2017	2018–2019
2016–2017	–	74.395 (22) [99.99%]
2018–2019	61.173 (15) [99.99%]	–

Table 6
Goodness-of-fit measures for all estimated models.

	Goodness-of-fit measures	**W-beam barriers**					**Cable barriers**				
		MNL	**GOL**	**RPL**	**RTRPGOL**	**RPLHMV**	**MNL**	**GOL**	**RPL**	**RTRPGOL**	**RPLHMV**
2016–	2017	Number of									
	observations	838	838	838	838	838	710	710	710	710	710
	Log-likelihood at zero	−721.80	−721.80	−721.80	−721.80	−721.80	−615.11	−615.11	−615.11	−615.11	−615.11
	Log-likelihood at convergence	−580.68	−602.78	−577.40	−592.30	−576.09	−451.19	−479.62	−446.99	−444.00	−440.91
	Adjusted R-Squared	0.175	0.145	0.178	0.159	0.179	0.245	0.196	0.250	0.237	0.258
	AIC	1203.360	1245.560	1198.800	1224.600	1198.180	944.380	1001.240	937.980	964.000	929.820
	AICc	1204.532	1246.628	1200.042	1225.628	1199.556	945.743	1002.543	939.473	968.417	931.552
BIC	1302.711	1346.911	1296.151	1325.951	1293.531	1040.251	1097.111	1031.851	1025.871	1019.691	
2018–	2019	Number of									
	observations	718	718	718	718	718	779	779	779	779	779
	Log-likelihood at zero	−609.47	−609.47	−609.47	−609.47	−609.47	−635.95	−635.95	−635.95	−635.95	−635.95
	Log-likelihood at convergence	−543.97	−550.68	−540.27	−516.04	−509.07	−474.81	−484.42	−468.27	−467.12	−441.92
	Adjusted R-Squared	0.078	0.070	0.081	0.106	0.114	0.228	0.212	0.238	0.240	0.270
	AIC	1133.940	1141.360	1132.540	1108.080	1100.140	999.620	1020.840	990.540	990.240	957.840
	AICc	1135.491	1142.605	1134.532	1112.465	1105.195	1001.326	1022.667	992.513	992.365	961.595
BIC	1239.199	1252.619	1231.799	1183.339	1169.399	1102.754		1121.974	1089.674	1087.374	1036.974

MNL: Multinomial logit model; RPL: Random parameters multinomial logit model; RPLHMV: Random parameters logit models with heterogeneity in means and variances; GOL: Generalized ordered logit model; RTRPGOL: Random thresholds random parameters generalized ordered logit model.

In all, the RPLHMV statistically outperforms the other five modeling alternatives, in terms of the selected goodness-of-fit measures. These results are in line with Balusu et al. (2018).

To further compare the two best performing models, the RPLHMV and RTRPGOL, the Ben-Akiva and Lerman's adjusted likelihood ratio (BL) test statistic is computed as follows (Ben-Akiva and Lerman 1985; Yasmin and Eluru, 2013):

$$\lambda = \Phi\left\{-\left[\sqrt{-2(\rho_2^2 - \rho_1^2)L(C) + (M_2 - M_1)}\right]\right\} \tag{13}$$

where, ρ_i^2 represents the McFadden's adjusted rho-square value for model i, $L(C)$ represents the log-likelihood at sample shares, M_i is the number of parameters in model i, and $\Phi(.)$ represents the cumulative standard normal distribution function. The resulting λ value for the comparison of the RPLHMV and RTRPHOL models is 0 in all traffic barrier models and across all years, clearly indicating that the RPLHMV model offers a statistically superior fit as compared to the RTRPGOL. These results are also in line with the Balusu et al. (2018) paper.

In the subsequent section, we discuss the results from the RPLHMV and RTRPGOL modeling frameworks.

6.2. Insights from the RPLHMV and RTRPGOL modeling frameworks.

The model estimation results for the w-beam barrier crashes are shown in Tables 7-8. For the 2016–2017 RPLHV model, the dark-lighted indicator in the minor injury severity outcome was significant as a normally distributed random parameter, wherein 73.35%[2] of the observations resulted in an increase in the probability of minor injury (and in a reduction in the rest 26.65%). W-beam barriers are far less rigid as compared to concrete barriers, with the former being more prone to causing the vehicle to rollover and run off the road in case of a collision. Consequently, more rigid barriers, such as concrete ones, may be more suitable for mountainous roads than w-beam barriers. In addition, proper caution signage ahead of dark-lighted locations can also help drivers avoid unnecessary improper braking and steering.

For the 2016–2017 RTRPGOL model, four variables – the constant, the truck indicator, the medium–low visibility indicator, and the sunny indicator – were significant as normally distributed random parameters. Specifically, driving a truck, or driving when visibility is poor (medium–low visibility conditions) increased the probability of more severe injury for 61.94% and 84.89% of the drivers, respectively. On the other hand, driving during sunny weather conditions reduced the probability of severe injury for 91.05% of the drivers. The threshold was a random parameter with a mean of 0.782, and a standard deviation of 3.766. Given these distributional parameters, the intercept for the threshold increased its value for 58.22% of the observations. In addition, three variables –the improper braking and steering, the over 55-mph speed limit, and the truck indicators – were found to decrease the value of the threshold and thus increase the probability of severe injury.

For the 2018–2019 RPLHMV model, the cloudy weather indicator and the novice driving experience (between 3 and 10 years) indicator in the minor injury severity outcome were significant as random parameters, with a low probability of minor injury for the majority of the observations (94.54% and 90.31%, respectively). The curved section indicator was found to increase the mean of the cloudy weather indicator, making minor injuries more likely. Furthermore, the weekend and dark-lighted indicators were found to increase the mean of this driving experience indicator, thus increasing the likelihood of minor injuries. Overall, nighttime (even lighted) crashes have been found in the literature to be related to injury (frequently severe) in mountainous regions. Our finding seems to be consistent with the literature (Wen and Xue, 2020; Yu et al., 2020a). To that end, highly efficient street lighting over long mountainous segments should be considered to improve visibility during nighttime conditions. Note that in the 2018–2019 period (Table 8), the variance of the novice driving experience (between 3 and 10 years) indicator in the minor injury severity outcome was found to be affected by the intersection indicators. The variable increased the variance of novice driving experience (between 3 and 10 years) in minor injury outcomes, reflecting higher variability.

For the 2018–2019 RTRPGOL model, three variables – the sunny indicator, the cloudy indicator, and the weekend indicator – were significant as normally distributed random parameters. Specifically, driving over the weekend, or during sunny or cloudy conditions reduced the probability of severe injury for 74.89%, 82.09%, and 79.19% of the drivers, respectively. The threshold resulted in a random parameter with a mean of 1.100, and a standard deviation of 0.897. Given these distributional parameters, the intercept for the threshold increased its value for 89.00% of the observations. And three variables – the weekend, the cloudy, and the dark-lighted indicators – were found to increase the value of the threshold and thus decrease the probability of severe injury.

The model estimation results for the cable barrier crashes are presented in Tables 9-10. For the 2016–2017 RPLHMV model, the curved section indicator in the minor injury severity outcome was statistically significant as a random parameter, where 89.80% of the crashes had an increase in the probability of no injury (and the rest had a reduction). The expert driving experience (15 years or greater) indicator was found to decrease the mean of the curved section indicator, making minor injuries less likely. Again, it should be noted that in 2016–2017 (Table 9), the variance of the curved section indicator in

[2] Because in random parameters with heterogeneity in the means, the mean of each parameter will change by observation, presenting the distributional split of the random parameter based on its mean and standard deviation of their normally distributed parameter density function is not applicable. For this reason, the vectors of generated parameters are observed post-estimation, and the number of betas above and below zero are reported. Caution, however, should be exercised when reporting these above and below zero values, as the parameter values are an approximation estimated with Bayesian techniques (Hou et al., 2022).

Table 7
Model results of RTRPGOL and RPLHMV for w-beam barrier crashes in 2016–2017 [No Injury (NI), Minor Injury (MI), and Severe Injury (SI)].

Variable	RPLHMV-NI		RPLHMV-MI		RPLHMV-SI		RTRPGOL	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constant	–	–	−1.466***	−3.61	−1.618***	−5.22	−1.831***	−3.86
Standard deviation of parameter density function	–	–	–	–	–	–	4.788***	3.72
Driver characteristics								
Driver under alcohol influence indicator (1 if driver under alcohol influence, 0 otherwise)	–	–	2.172***	5.69	–	–	1.076***	4.74
No driver seatbelt use indicator (1 if driver without seatbelt, 0 otherwise)	–	–	–	–	1.878***	3.67	1.141**	2.00
Vehicle characteristics								
Truck indicator (1 if truck, 0 otherwise)	–	–	–	–	0.644***	3.17	1.354*	1.73
Standard deviation of parameter density function	–	–	–	–			4.457**	2.23
Non local vehicle indicator (1 if non-local vehicles, 0 otherwise)	–	–	–	–	0.515**	1.98	0.705***	2.98
Roadway characteristics								
Homogeneous section indicator (1 if crash occurred in a homogeneous section, 0 otherwise)	–	–	−0.541**	−2.05	–	–	−0.379	−1.63
Ramp indicator (1 if crash occurred in ramp, 0 otherwise)	–	–	–	–	0.697**	2.47	0.184	0.54
Curved indicator (1 if crash occurred in curved segments, 0 otherwise)	1.084***	4.29	–	–	–	–	−0.179	−0.87
Wet surface indicator (1 if road surface condition was wet, 0 otherwise)	–	–	–	–	−1.527**	−1.98	−1.376**	−2.37
Speed limit indicator (1 if speed limit > 55 mph, 0 otherwise)	–	–	–	–	2.268***	5.70	1.076***	4.74
Environment characteristics								
Daylight indicator (1 if daylight, 0 otherwise)	–	–	–	–	0.764**	2.11	0.686**	2.16
Dark lighted indicator (1 if dark lighted, 0 otherwise)	–	–	0.841***	2.66	–	–	−0.038	−0.21
Standard deviation of parameter density function	–	–	1.349*	1.78	–	–	–	–
Medium-low visibility indicator (1 if visibility between 50 and 100 m, 0 otherwise)	–	–	–	–	0.746***	3.66	2.652***	3.88
Standard deviation of parameter density function	–	–	–	–	–	–	2.570*	1.82
Sunny indicator (1 if sunny, 0 otherwise)	–	–	–	–	−1.231***	−4.99	−4.257**	−2.44
Standard deviation of parameter density function	–	–	–	–	–	–	3.168**	2.28
μ	–	–	–	–			0.782***	2.64
Standard deviation of parameter density function	–	–	–	–			3.766***	9.65
Threshold covariates								
Improper braking and steering indicator (1 if improper breaking and steering, 0 otherwise)	–	–	–	–	–	–	−1.104***	−5.57
Speed limit indicator (1 if speed limit > 55 mph, 0 otherwise)	–	–	–	–	–	–	−1.257***	−4.27
Truck indicator (1 if truck, 0 otherwise)	–	–	–	–	–	–	−1.900**	−4.40

***, **, * ==> Significance at 0.99, 0.95, and 0.90 level of confidence, respectively.
RPLHMV: Random parameters logit model with heterogeneity in the means and variances model.
RTRPGOL: Random thresholds random parameters generalized ordered logit model.

the minor injury severity outcome is affected by the high visibility indicator (visibility greater than 200 m), which increases its variance (it makes the tail of the distribution of the parameter density function flatter, and thus offers a more uniformly shaped distribution of the betas). This finding may be capturing the effect of drivers that perceive the high visibility conditions on the curved section as safe (or low risk), in which case they are driving less carefully or with a lower level of alertness.

For the 2016–2017 RTRPGOL model, three variables – the homogeneous section indicator, the curved indicator, and the daylight indicator – were significant as normally distributed random parameters. Specifically, driving on homogeneous sections or sections with curves increased the probability of severe injury for 66.75% and 65.61% of the drivers, respectively. On the other hand, driving during daylight reduced the probability of severe injury for 56.00% of the drivers. The threshold was a random parameter with a mean of 1.418, and a standard deviation of 2.333. Given these distributional parameters, the intercept for the threshold increased its value for 72.83% of the observations. In addition, three variables – the over 55-mph speed limit, no driver seatbelt use, and the truck indicators – were found to decrease the value of the threshold and thus increase the probability of severe injury.

For the 2018–2019 RPLHMV models, the medium–low visibility (between 50 and 100 m) and the dark-lighted indicators in the no injury severity outcome were statistically significant as random parameters. Specifically, in 87.78% of the observations, the medium–low visibility (between 50 and 100 m) indicator resulted in an increase in the probability of no injury (and in a reduction in the rest 27.09%); whereas, in 87.08% of the observations, the dark lighted indicator resulted in a reduction in the probability of no injury (and in an increase in the rest 12.92%). The rainy/snowy/foggy weather indicator and the winter season indicator were found to increase the mean of the medium–low visibility indicator, making no injuries more likely. The curved section indicator was found to decrease the mean of the medium–low visibility indicator, making no injuries less likely. The curved section and summer season indicators were found to increase the mean of the dark with road

Table 8
Model results of RPLHMV and RTRPGOL for w-beam barrier crashes in 2018–2019 [No Injury (NI), Minor Injury (MI), and Severe Injury (SI)].

Variable	RPLHMV-NI		RPLHMV-MI		RPLHMV-SI		RTRPGOL	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constant	–	–	−2.094***	−6.84	−1.809***	−6.47	0.644***	2.62
Driver characteristics								
Driver under alcohol influence indicator (1 if driver under alcohol influence, 0 otherwise)	–	–	3.521***	4.65	–	–	–	–
No driver seatbelt use indicator (1 if driver without seatbelt, 0 otherwise)	–	–	–	–	2.013***	6.38	0.979***	3.33
Novice driving experience indicator (1 if driving experience between 3 and 10 years, 0 otherwise)	–	–	−5.198**	−2.50	–	–	−0.342	−1.41
Standard deviation of parameter density function	–	–	4.000**	2.43	–	–	–	–
Heterogeneity in the mean of random parameter								
Novice driving experience indicator (1 if driving experience between 3 and 10 years, 0 otherwise): Weekends indicator (1 if crash occurred during the weekends, 0 otherwise)	–	–	3.312***	2.59	–	–	–	–
Novice driving experience indicator (1 if driving experience between 3 and 10 years, 0 otherwise): Dark-no light indicator (1 if dark-no light, 0)	–	–	2.973*	1.84	–	–	–	–
Novice driving experience indicator (1 if driving experience between 3 and 10 years, 0 otherwise): Dark lighted indicator (1 if dark lighted, 0)	–	–	5.071**	2.47	–	–	–	–
Heterogeneity in the variance of random parameter								
Novice driving experience indicator (1 if driving experience between 3 and 10 years, 0 otherwise): Intersection indicator (1 if intersection, 0)	–	–	1.164*	1.93	–	–	–	–
Vehicle characteristics								
Truck indicator (1 if truck, 0 otherwise)	–	–	–	–	1.106***	3.77	1.200***	5.13
Roadway characteristics								
Homogeneous section indicator (1 if crash occurred in a homogeneous section, 0 otherwise)	–	–	−1.440**	−2.34	–	–	−0.399	−1.48
Ramp indicator (1 if crash occurred in ramp, 0 otherwise)	–	–	–	–	1.000**	2.56	0.492	1.17
Curved indicator (1 if crash occurred in curved segments, 0 otherwise)	0.513*	1.79	–	–	–	–	0.034	0.17
Wet surface indicator (1 if road surface condition was wet, 0 otherwise)	–	–	–	–	−0.724**	−2.29	−1.009***	−3.60
Speed limit indicator (1 if speed limit > 55 mph, 0 otherwise)	–	–	–	–	1.659***	3.11	0.694***	2.92
Environment characteristics								
Daylight indicator (1 if daylight, 0 otherwise)	–	–	–	–	0.507*	1.67	1.094***	4.21
Low visibility indicator (1 if visibility below 50 m, 0 otherwise)	–	–	–	–	1.898*	1.72	0.427	1.26
Medium visibility indicator (1 if visibility between 100 and 200 m, 0 otherwise)	–	–	−0.875*	−1.76	−1.237**	−2.49	0.024	0.11
Sunny indicator (1 if sunny, 0 otherwise)	–	–	–	–	–	–	−3.789***	−3.68
Standard deviation of parameter density function	–	–	–	–	–	–	4.124***	3.43
Cloudy indicator (1 if cloudy, 0 otherwise)	–	–	−2.644**	−2.14	–	–	−7.082**	−2.51
Standard deviation of parameter density function	–	–	1.651*	1.70	–	–	8.710***	2.66
Heterogeneity in the mean of random parameter								
Cloudy indicator (1 if cloudy, 0 otherwise): Curved indicator (1 if crash occurred in curved segment, 0 otherwise)	–	–	1.089*	1.92	–	–	–	–
Weekends indicator (1 if crash occurred during the weekends, 0 otherwise)	–	–	–	–	−0.646*	−1.91	−1.584***	−3.45
Standard deviation of parameter density function	–	–	–	–	–	–	2.360***	3.06
μ	–	–	–	–	–	–	1.100***	4.96
Standard deviation of parameter density function	–	–	–	–	–	–	0.897*	1.87
Threshold covariates								
Weekends indicator (1 if crash occurred during the weekends, 0 otherwise)	–	–	–	–	–	–	0.502**	2.56
Cloudy indicator (1 if cloudy, 0 otherwise)	–	–	–	–	–	–	0.483*	1.91
Dark lighted indicator (1 if dark lighted, 0 otherwise)	–	–	–	–	–	–	0.682***	3.93

***, **, * ==> Significance at 0.99, 0.95, and 0.90 level of confidence, respectively.
RPLHMV: Random parameters logit model with heterogeneity in the means and variances model.
RTRPGOL: Random thresholds random parameters generalized ordered logit model.

streetlights indicator, making no injuries more likely; whereas, the winter season indicator was found to decrease the mean of the darkness with road streetlights indicator, making no injuries less likely.

For the 2018–2019 RTRPGOL models, two variables –the curved indicator and the dark-lighted indicator – were significant as normally distributed random parameters. Specifically, driving on sections with curves increased the probability of

Table 9
Model results of RTRPGOL and RPLHMV for cable barrier crashes in 2016–2017 [No Injury (NI), Minor Injury (MI), and Severe Injury (SI)].

Variable	RPLHMV-NI		RPLHMV-MI		RPLHMV-SI		RTRPGOL	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constant	1.198**	1.98	1.194**	2.10	–	–	−0.759***	−3.51
Driver characteristics								
Driver under alcohol influence indicator (1 if driver under alcohol influence, 0 otherwise)	–	–	1.013***	3.16	–	–	0.802***	2.77
No driver seatbelt use indicator (1 if driver without seatbelt, 0 otherwise)	–	–	–	–	1.529***	3.07	0.258	0.85
Vehicle characteristics								
Truck indicator (1 if truck, 0 otherwise)	–	–	–	–	−2.306***	−4.25	−0.059	−0.24
Roadway characteristics								
Homogeneous section indicator (1 if crash occurred in a homogeneous section, 0 otherwise)	–	–	−1.403***	−7.69	–	–	−1.061**	−2.45
Standard deviation of parameter density function	–	–	–	–	–	–	1.498***	2.80
Curved indicator (1 if crash occurred in curved segment, 0 otherwise)	–	–	1.753***	3.27	–	–	2.234***	3.50
Standard deviation of parameter density function	–	–	1.380***	2.65	–	–	5.560***	2.91
Heterogeneity in the mean of random parameter								
Curved indicator (1 if crash occurred in curved segment, 0 otherwise): Expert driving experience indicator (1 if driving experience above 15 years, 0 otherwise)	–	–	−0.993**	−2.28	–	–	–	–
Heterogeneity in the variance of random parameter								
Curved indicator (1 if crash occurred in curved segment, 0 otherwise): High visibility indicator (1 if visibility above 200 m, 0 otherwise)	–	–	1.435***	2.91	–	–	–	–
Speed limit indicator (1 if speed limit > 55 mph, 0 otherwise)	–	–	–	–	−2.176***	−3.92	1.556***	5.29
Environment characteristics								
Daylight indicator (1 if daylight, 0 otherwise)	–	–	–	–	−1.129***	−4.82	−0.994**	−1.96
Standard deviation of parameter density function	–	–	–	–	–	–	6.582***	3.89
Medium visibility indicator (1 if visibility between 100 and 200 m, 0 otherwise)	–	–	–	–	−0.968**	−2.17	−0.641***	−2.70
High visibility indicator (1 if visibility above 200 m, 0 otherwise)	–	–	–	–	−1.247**	−2.47	−0.032	−0.11
Summer indicator (1 if summer, 0 otherwise)	–	–	−0.777***	−2.94	–	–	−0.220	−0.97
Early morning indicator (1 if time 00:00–7:00, 0 otherwise)	–	–	0.964***	3.02	1.249***	2.59	0.756**	2.41
Daytime off-peak indicator (1 if time 9:00–16:59, 0 otherwise)	0.770***	3.28	–	–	–	–	−0.473	−1.59
μ	–	–	–	–	–	–	1.418***	5.37
Standard deviation of parameter density function	–	–	–	–	–	–	2.333***	3.41
Threshold covariates								
Speed limit indicator (1 if speed limit > 55 mph, 0 otherwise)	–	–	–	–	–	–	−1.123***	−3.65
No driver seatbelt use indicator (1 if driver without seatbelt, 0 otherwise)	–	–	–	–	–	–	−0.520*	−1.83
Truck indicator (1 if truck, 0 otherwise)	–	–	–	–	–	–	−1.290***	−4.01

***, **, * ==>Significance at 0.99, 0.95, and 0.90 level of confidence, respectively.
RPLHMV: Random parameters logit model with heterogeneity in the means and variances model.
RTRPGOL: Random thresholds random parameters generalized ordered logit model.

severe injury for 99.24% of the drivers. Whereas, driving during dark-lighted conditions reduced the probability of severe injury for 68.33% of the drivers. The threshold was a random parameter with a mean of 1.509, and a standard deviation of 0.841. Given these distributional parameters, the intercept for the threshold increased its value for 96.36% of observations. And two variables were found to parametrically affect the threshold. The dark-lighted indicator increased the value of the threshold and thus decreased the probability of severe injury; while the truck indicator decreased the value of the threshold and thus increased the probability of severe injury.

6.3. Different effects of factors determining the driver injury-severity of crashes

In this section, the statistically superior RPLHMV model is leveraged to quantitatively describe the impact of explanatory variables on the driver injury-severity, and explore how these factors change over the years (between 2016–2017 and 2018–2019). The model estimation results indicate that several drivers-, vehicles-, road-, and environment-specific characteristics significantly affect the injury-severity of drivers. Table 11 provides their magnitudes (derived from their pseudo-elasticities) on injury severities with respect to the two traffic barrier types (w-beam and cable) in mountainous regions for the 2016–2017 and 2018–2019 models. The crash injury-severities and the effects of explanatory variables vary across traffic barriers and different periods for the same traffic barrier. To that end, statistically significant variables that show temporally stable elasticities are likely more important for formulating long-term strategies to enhance traffic safety on mountainous roads.

Table 10
Model results of RTRPGOL and RPLHMV for cable barrier crashes in 2018–2019 [No Injury (NI), Minor Injury (MI), and Severe Injury (SI)].

Variable	RPLHMV-NI		RPLHMV-MI		RPLHMV-SI		RTRPGOL	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constant	−1.663***	−4.15	−1.414***	−3.21	–	–	−1.763***	−6.82
Driver characteristics								
Driver under alcohol influence indicator (1 if driver under alcohol influence, 0 otherwise)	–	–	0.948***	3.39	–	–	0.090	0.32
No driver seatbelt use indicator (1 if driver without seatbelt, 0 otherwise)	–	–	–	–	1.096**	2.38	0.545*	1.80
Vehicle characteristics								
Truck indicator (1 if truck, 0 otherwise)	–	–	–	–	−2.369***	−4.94	−0.941	−0.80
Roadway characteristics								
Homogeneous section indicator (1 if crash occurred in a homogeneous section, 0 otherwise)	–	–	−1.290***	−4.75	–	–	−1.784**	−2.00
Curved indicator (1 if crash occurred in curved segment, 0 otherwise)	–	–	0.708*	1.79	–	–	1.239***	3.36
Standard deviation of parameter density function	–	–	–	–			1.371*	1.71
Speed limit indicator (1 if speed limit > 55 mph, 0 otherwise)	–	–	–	–	−0.787**	−2.20	0.565**	2.26
Environment characteristics								
Daylight indicator (1 if daylight, 0 otherwise)	–	–	–	–	−1.291***	−4.77	–	–
Dark lighted indicator (1 if dark lighted, 0 otherwise)	−2.851***	−4.03	–	–	–	–	−6.385*	−1.94
Standard deviation of parameter density function	2.523***	2.79	–	–	–	–	13.388**	2.51
Heterogeneity in the mean of random parameter								
Dark lighted indicator (1 if dark lighted, 0 otherwise): Curved indicator (1 if crash occurred in curved segment, 0 otherwise)	1.175*	1.67	–	–	–	–	–	–
Dark lighted indicator (1 if dark lighted, 0 otherwise): Winter indicator (1 if winter, 0 otherwise)	−2.554***	−2.85	–	–	–	–	–	–
Dark lighted indicator (1 if dark lighted, 0 otherwise): Summer indicator (1 if summer, 0 otherwise)	1.889**	2.23	–	–	–	–	–	–
Medium-low visibility indicator (1 if visibility between 50 and 100 m, 0 otherwise)	2.003***	2.81	–	–	–	–	1.087**	2.07
Standard deviation of parameter density function	1.721*	1.93	–	–	–	–	–	–
Heterogeneity in the mean of random parameter								
Medium-low visibility indicator (1 if visibility between 50 and 100 m, 0 otherwise): Curved indicator (1 if crash occurred in curved segment, 0 otherwise)	−2.210***	−3.14	–	–	–	–	–	–
Medium-low visibility indicator (1 if visibility between 50 and 100 m, 0 otherwise): Rainy/snowy/foggy indicator (1 if rainy/snowy/foggy, 0 otherwise)	1.643**	2.01	–	–	–	–	–	–
Medium-low visibility indicator (1 if visibility between 50 and 100 m, 0 otherwise): Winter indicator (1 if winter, 0 otherwise)	1.757**	2.15	–	–	–	–	–	–
Sunny indicator (1 if sunny, 0 otherwise)	–	–	–	–	−0.675*	−1.92	−0.268	−0.86
Summer indicator (1 if summer, 0 otherwise)	–	–	−1.189***	−2.94	–	–	−0.676***	−2.88
μ	–	–	–	–	–	–	1.509***	6.14
Standard deviation of parameter density function	–	–	–	–	–	–	0.841***	2.59
Threshold covariates								
Dark lighted indicator (1 if dark lighted, 0 otherwise)	–	–	–	–	–	–	1.740***	3.08
Truck indicator (1 if truck, 0 otherwise)	–	–	–	–	–	–	−1.900***	−4.15

*** **, * ==> Significance at 0.99, 0.95, and 0.90 level of confidence, respectively.
RPLHMV: Random parameters logit model with heterogeneity in the means and variances model.
RTRPGOL: Random thresholds random parameters generalized ordered logit model.

Table 11 directly compares the effect of the relative temporal stability variables across traffic barrier types, injury severity levels, and years.

6.3.1. Driver characteristics

As shown in Table 11, there are two statistically significant driver-related variables that exhibit relative temporal stability. Among them, driving while drunk and unbelted (without wearing a seat belt) consistently affects all traffic barrier crashes.

Both drunk and unbelted drivers are associated with an increased likelihood of severe injuries in all traffic barrier crashes in mountainous regions. Alcohol can paralyze drivers' nerves and impair their control ability (Yan et al., 2022), which is critical in avoiding traffic barrier crashes. The use of seat belts can protect the driver from secondary impact injuries by restraining them in their seat and preventing them from rushing forward when the vehicle impacts the traffic barriers. Consequently, enforcement and, possibly, increasing penalties for such risk-driving behavior (drunk and unbelted driving) is likely going to improve mountainous road safety.

Table 11
Comparison of the effects of the independent variables (and their magnitudes, as derived from their pseudo-elasticities (%)) on injury severities with respect to the two traffic barrier crashes in mountainous regions for the 2016–2017 and 2018–2019 models.

Variable	W-beam barriers						Cable barriers					
	2016–2017			2018–2019			2016–2017			2018–2019		
	SI	MI	NI	SI	MI	NI	SI	MI	NI	SI	MI	NI
Driver characteristics												
Driver under alcohol influence indicator (1 if driver under alcohol influence, 0 otherwise) [MI]	−65.42	30.46	−60.33	−23.09	14.36	−16.24	−12.16	3.32	−8.18	−18.18	4.09	−18.18
No driver seatbelt use indicator (1 if driver without seatbelt, 0 otherwise) [SI]	1.25	−6.07	−6.37	14.68	−56.64	−56.64	11.20	−5.39	−3.14	8.94	−2.74	−1.82
Novice driving experience indicator (1 if driving experience between 3 and 10 years, 0 otherwise) [MI]	–	–	–	0.61	−11.56	−1.94	–	–	–	–	–	–
Vehicle characteristics												
Truck indicator (1 if truck, 0 otherwise) [SI]	10.89	−5.66	−5.77	4.31	−9.06	−9.06	−29.03	3.78	2.25	−34.98	1.74	1.03
Non local vehicle indicator (1 if non-local vehicles, 0 otherwise) [SI]	4.59	−2.28	−2.35	–	–	–	–	–	–	–	–	–
Roadway characteristics												
Homogeneous section indicator (1 if crash occurred in a homogeneous section, 0 otherwise) [MI]	4.67	−28.91	4.67	2.11	−13.82	1.64	0.34	−4.37	0.37	35.72	−65.62	18.55
Ramp indicator (1 if crash occurred in ramp, 0 otherwise) [SI]	3.14	−7.16	−7.66	2.73	−10.33	−10.33	–	–	–	–	–	–
Curved indicator (1 if crash occurred in curved segment, 0 otherwise) [MI]	–	–	–	–	–	–	−6.79	12.38	−6.79	−16.43	30.91	−7.98
Curved indicator (1 if crash occurred in curved segment, 0 otherwise) [NI]	−41.23	−41.23	18.18	−11.75	−7.43	2.96	–	–	–	–	–	–
Wet surface indicator (1 if road surface condition was wet, 0 otherwise) [SI]	−4.37	0.34	0.37	−14.03	1.62	0.91	–	–	–	–	–	–
Speed limit indicator (1 if speed limit > 55 mph, 0 otherwise) [SI]	76.67	−22.52	−23.46	30.59	−9.59	−3.56	−35.56	2.16	1.72	−24.12	2.16	1.72
Environment characteristics												
Daylight indicator (1 if daylight, 0 otherwise) [SI]	7.45	−3.53	−3.05	6.88	−1.37	−2.00	−35.25	3.30	4.51	−58.01	5.20	3.37
Dark lighted indicator (1 if dark lighted, 0 otherwise) [MI]	−10.96	35.47	−10.96	–	–	–	–	–	–	–	–	–
Dark lighted indicator (1 if dark lighted, 0 otherwise) [NI]	–	–	–	–	–	–	–	–	–	20.03	20.03	−17.83
Low visibility indicator (1 if visibility below 50 m, 0 otherwise) [SI]	–	–	–	2.30	−0.28	−2.02	–	–	–	–	–	–
Medium-low visibility indicator (1 if visibility between 50 and 100 m, 0 otherwise) [SI]	3.57	−0.42	−3.16	–	–	–	–	–	–	–	–	–
Medium-low visibility indicator (1 if visibility between 50 and 100 m, 0 otherwise) [NI]	–	–	–	–	–	–	–	–	–	−0.40	−3.25	3.65
Medium visibility indicator (1 if visibility between 100 and 200 m, 0 otherwise) [SI]	–	–	–	−1.25	0.36	0.89	−1.22	0.23	1.00	–	–	–

Table 11 (*continued*)

Variable	W-beam barriers						Cable barriers					
	2016–2017			2018–2019			2016–2017			2018–2019		
	SI	MI	NI	SI	MI	NI	SI	MI	NI	SI	MI	NI
Medium visibility indicator (1 if visibility between 100 and 200 m, 0 otherwise) [MI]	–	–	–	0.20	−1.30	1.09	–	–	–	–	–	–
High visibility indicator (1 if visibility above 200 m, 0 otherwise) [MI]	–	–	–	–	–	–	0.84	−1.50	0.66	–	–	–
Sunny indicator (1 if sunny, 0 otherwise) [SI]	−2.97	0.18	2.78	–	–	–	–	–	–	−1.06	0.20	0.86
Cloudy indicator (1 if cloudy, 0 otherwise) [MI]	–	–	–	0.39	−0.67	0.28	–	–	–	–	–	–
Summer indicator (1 if summer, 0 otherwise) [MI]	–	–	–	–	–	–	0.39	−1.12	0.74	0.24	−1.34	1.10
Early morning indicator (1 if time 00:00–7:00, 0 otherwise) [SI]	–	–	–	–	–	–	2.27	−1.30	−0.97	–	–	–
Early morning indicator (1 if time 00:00–7:00, 0 otherwise) [MI]	–	–	–	–	–	–	−1.00	2.94	−1.94	–	–	–
Daytime off-peak indicator (1 if time 9:00–16:59, 0 otherwise) [NI]	–	–	–	–	–	–	−0.75	−3.25	3.99	–	–	–
Weekends indicator (1 if crash occurred during the weekends, 0 otherwise) [SI]	–	–	–	−1.06	0.25	0.82	–	–	–	–	–	–

6.3.2. Vehicle characteristics

As shown in Table 11, there is only one statistically significant vehicle-related variable that exhibits relative temporal stability. The truck indicator is found to have the opposite effect on different traffic barrier crashes: it is found to increase the likelihood of severe injuries in w-beam barrier models, while it decreases the likelihood of severe injuries in the cable barrier model. The large size and heavy weight of trucks increase the kinetic energy when hitting w-beam barriers. Cable barriers may effectively absorb the energy from the collision with trucks and result in low occupant impact force due to their flexible properties.

6.3.3. Roadway characteristics

Table 11 shows that there are five statistically significant roadway-related variables that exhibit relative temporal stability. Among them, the homogeneous section indicator has a consistent effect in all traffic barrier crashes. Ramp sections and wet surfaces have a significant effect only in w-beam barrier crashes. The speed limit (segments with a speed limit greater than 55mph) and the curved section indicator have the opposite effect on different traffic barrier crashes.

The homogeneous section indicator is found to be negatively associated with severe injuries in all traffic barrier models. In other words, heterogeneous sections, whose geometrical characteristics (i.e., number of lanes, roadway width, etc.) change throughout the length of the segment, increase the likelihood of severe injuries in all traffic barrier crashes in mountainous regions. Consequently, warning signs should be used in front of heterogeneous sections to warn drivers of potential hazards.

Furthermore, the ramp section indicator is found to increase the likelihood of severe injuries only in w-beam barrier crashes. The main cause of a high severe injury rate on ramp sections may be attributed to design misconfigurations of w-beam barriers, especially for traffic barrier end treatments (Molan et al., 2021a). End treatments are critical in the occurrence of traffic barrier crashes, because they may increase the potential of a vehicle rollover due to their configurations. Accordingly, road authorities should take reasonable measures to account for their limitations (e.g., through the use of blunt and turned-down end terminals of w-beam barriers).

Moreover, wet surfaces are found to reduce the likelihood of minor injuries in the w-beam models. This is in line with previous studies that have associated wet surface conditions with a reduced likelihood of severe injuries, due to the drivers' speed reducing their speed to compensate for the seemingly reduced friction due to the wet conditions (Fountas et al., 2021; Fountas and Anastasopoulos, 2017; Islam and Mannering, 2021).

Lastly, segments with curves and segments with high-speed limits (greater than 55mph) are found to have the opposite effect on different traffic barrier crashes. Curved segments increase the likelihood of no injuries in the w-beam barrier model, while they increase the likelihood of minor injuries in the cable barrier model. A curved segment is more likely to be associated with a run-off-road crash. At the same time, cable barriers are far less rigid than semi-flexible or rigid barriers, with the former being more prone to causing the vehicle to rollover and run off the road in case of a collision. Consequently, more

Table 12
Proposed strategies and proper resource allocation based on study findings.

	W-beam	Cable	Guidelines
The opposite effect between different traffic barrier crashes			
Curved section	↓	↑	Cable barriers are not suitable for curved sections; they can cause the vehicle to run off the road in case of a collision.
Speed limit (>55mph)	↑	↓	The higher speed increases the kinetic energy in crashes. Buffered cable barriers may partially absorb the energy to reduce drivers' injury-severity, as compared to w-beam barriers.
Truck	↑	↓	The large size and heavy weight of trucks increase the kinetic energy when hitting w-beam barriers. Cable barriers may effectively absorb the energy from the collision with trucks and result in low occupant impact force due to their flexible properties.
Daylight	↑	↓	Higher speed of vehicles during daylight may increase the impact energy in crashes involving less buffered w-beam barriers.
Single effect in one type of traffic barrier crashes			
Summer		↓	The summer indicator decreases the likelihood of severe injuries in the cable barrier model.
Ramp section	↑		Road authorities should take reasonable measures to minimize hazards associated with blunt or turn-down end terminals of w-beam barriers for ramp segments.
Wet surfaces	↓		Attention should be exercised on dry surfaces, as they increase injury severity in w-beam barrier crashes due to reduced buffering.
Consistent effect in all traffic barrier crashes			
Driver under alcohol influence	↑	↑	Enforcement and education programs about drunk and unbelted drivers should be enhanced.
No driver seatbelt use	↑	↑	
Homogeneous section	↓	↓	Warning signs should be considered in front of heterogeneous sections to warn drivers of potential hazards.

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

rigid barriers, such as concrete barriers, may be more suitable for curved roads instead of cable barriers. In addition, segments with high-speed limits (greater than 55mph) have lower severity crashes involving cable barriers, and higher severity crashes involving w-beam barriers. The reason for lower severity cable barrier crashes in higher-speed limit segments can be attributed to the reduced buffering. The higher speed increases the kinetic energy in crashes. Buffered cable barriers may partially absorb the energy to reduce drivers' injury-severity as compared to w-beam barriers.

6.3.4. Environmental characteristics

Table 11 shows that there are two statistically significant environment-related variables that exhibit relative temporal stability. Among them, the daylight indicator is found to have the opposite effect on different traffic barrier crashes. And the summer indicator has a significant effect only in cable barrier crashes.

The daylight indicator increases the likelihood of severe injuries in the w-beam barrier model, while it decreases the likelihood of severe injuries in the cable barrier model. As compared to cable barriers that are flexible, w-beam barriers cannot effectively absorb the energy from a crash due to their semi-rigid properties. In addition, the summer indicator decreases the likelihood of severe injuries in the cable barrier model.

In view of the existing mountainous traffic barrier safety challenges, we present in Table 12 a set of strategies based on the findings from the model estimation results of this paper.

7. Conclusion

Using crash data from mountainous regions in Guiyang City, China, from 2016 to 2019, this paper provides an empirical assessment of the performance of ordered and unordered discrete outcome models for examining the impact of exogenous factors determining the driver injury-severity of crashes involving two types of traffic barrier in mountainous regions: w-beam barriers and cable barriers. To that end, six different models were estimated: (1) GOL, (2) RTRPGOL, (3) MNL, (4) RPL, (5) RPLHM, and (6) RPLHMV model. The analysis went beyond a traditional cause-and-effect study by investigating how these effects changed over time and across traffic barrier types. Three driver-injury levels were considered: no injury, minor injury, and severe injury. The results of the estimated models showed that a wide variety of driver-, vehicle-, road-, and environment-specific characteristics affect driver injury-severity. The key findings are summarized as follows:

(1) The model comparison results show that the MNL model is found to statistically outperform (although, marginally) the GOL model in terms of goodness-of-fit measures, and the RTRPGOL model is statistically superior to the MNL and RPL models. However, the RPLHMV model statistically outperforms the RTRPGOL model. To that end, the superior RPLHMV model is leveraged to quantitatively describe the impact of explanatory variables on the driver injury-severity, and investigate how these effects changed over time and across traffic barrier types. In addition, the results of the temporal effects analysis show that some variables present relative temporal stability, which is important for formulating long-term strategies to enhance traffic safety on mountainous roads.

(2) The effects of the explanatory factors that exhibit relative temporal stability are found to vary across different traffic barrier types.
   (a) First, four explanatory variables are found to have the opposite effect on different traffic barrier crashes. For example, the variables representing high-speed limits, high proportion of large trucks, and daylight, all increase the likelihood of severe injuries in the w-beam barrier model, while they decrease the likelihood of severe injuries in the cable barrier model. The curved section indicator decreases the likelihood of severe injuries in the w-beam barrier model, and increases the likelihood of severe injuries in the cable barrier model.
   (b) Second, a number of explanatory variables are found to have a significant effect in only one type of traffic barrier crashes. For w-beam barrier crashes, the ramp section and dry surfaces indicators increase the likelihood of severe injuries.
   (c) Third, variables reflecting drunk drivers, unbelted drivers, and heterogeneous segments, are all found to increase the injury severity of all traffic barrier crashes.

The findings from this analysis also offer a number of practical implications. First, this study provided an empirical assessment of the performance of ordered and unordered discrete outcome models, which may be helpful in choosing a suitable way to model traffic barrier crash data. In addition, the study also untangled the multilayered role of unobserved heterogeneity in traffic barrier crashes. Decision-makers can gain deeper insights into the factors influencing the injury severity of traffic barrier crashes and develop more reasonable countermeasures to reduce injury severity.[3] Second, this study revealed different effects of explanatory variables on different traffic barrier crashes. The results from this study are expected to help policymakers to take necessary measures in reducing traffic barrier crashes in mountainous regions by forming appropriate strategies and by allocating properly their available resources at the pre-planning phase (see Table 12).

This study also has some limitations. For example, the factors affecting the injury-severities of crashes involving rigid-type barriers (e.g., concrete barriers) or end-treatments could be further explored with the collection of additional data that include their detailed geometric characteristics. Another research avenue is to investigate crashes involving additional roadside barrier types in both urban and rural settings. This will provide a more comprehensive overview of the differences among crash-injury severities involving various roadside barriers, and will help devise appropriate protection measures to minimize crash injury-severity in mountainous regions.

Data availability

Data will be made available on request.

Declaration of Competing Interest

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

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References

Transportation Officials, 2011. Subcommittee on Bridges. AASHTO guide specifications for LRFD seismic bridge design. AASHTO.
Ahmed, S., Pantangi, S., Eker, U., Fountas, G., Still, S.E., Anastasopoulos, P., 2020. Analysis of safety benefits and security concerns from the use of autonomous vehicles: a grouped random parameters bivariate probit approach with heterogeneity in means. Anal. Methods in Accid. Res. 100134.
Ahmed, S., Cohen, J., Anastasopoulos, P., 2021a. A correlated random parameters with heterogeneity in means approach of deer-vehicle collisions and resulting injury-severities. Analytic Methods Accident Res. 30, 100160.
Ahmed, S., Fountas, G., Eker, U., Anastasopoulos, P., 2021b. Are we willing to relocate with the future introduction of flying cars? An exploratory empirical analysis of public perceptions in the United States. Transport Sci., 1–50
Ahmed, S., Fountas, G., Eker, U., Still, S.E., Anastasopoulos, P., 2021c. An exploratory empirical analysis of willingness to hire and pay for flying taxis and shared flying car services. J. Air Transp. Manag. 90, 101963.
Alnawmasi, N., Mannering, F., 2019. A statistical assessment of temporal instability in the factors determining motorcyclist injury severities. Anal. Methods in Accid. Res. 22, 100090.
Amiri, A.M., Sadri, A., Nadimi, N., Shams, M., 2020. A comparison between artificial neural network and hybrid intelligent genetic algorithm in predicting the severity of fixed object crashes among elderly drivers. Accid. Anal. Prev. 138, 105468.
Anastasopoulos, P., Mannering, F., 2011. An empirical assessment of fixed and random parameter logit models using crash- and non-crash-specific injury data. Accid. Anal. Prev. 43 (3), 1140–1147.
Balusu, S., Pinjari, A., Mannering, F., Eluru, N., 2018. Non-decreasing threshold variances in mixed generalized ordered response models: a negative correlations approach to variance reduction. Anal. Methods in Accid. Res. 20, 46–67.

[3] A few examples include: improving the lighting conditions of the accident-prone mountainous roads; increasing the mileage of street lighting on mountainous dark lighted regions; and using caution signage on high-risk locations on mountainous regions to prevent accidents due to improper braking and steering.

Behnood, A., Mannering, F., 2015. The temporal stability of factors affecting driver-injury severities in single-vehicle crashes: some empirical evidence. Anal. Methods in Accid. Res. 8, 7–32.
Behnood, A., Mannering, F., 2017a. Determinants of bicyclist injury severities in bicycle-vehicle crashes: a random parameters approach with heterogeneity in means and variances. Anal. Methods in Accid. Res. 16, 35–47.
Behnood, A., Mannering, F., 2017b. The effect of passengers on driver-injury severities in single-vehicle crashes: a random parameters heterogeneity-in-means approach. Anal. Methods in Accid. Res. 14, 41–53.
Behnood, A., Mannering, F., 2019. Time-of-day variations and temporal instability of factors affecting injury severities in large-truck crashes. Anal. Methods in Accid. Res. 23, 100102.
Ben-Akiva, M.E., Lerman, R.S., 1985. Discrete Choice Analysis: Theory and Application to Travel Demand. The MIT Press, Cambridge.
Bhowmik, T., Yasmin, S., Eluru, N., 2019a. A multilevel generalized ordered probit fractional split model for analyzing vehicle speed. Anal. Methods in Accid. Res. 21, 13–31.
Bhowmik, T., Yasmin, S., Eluru, N., 2019b. Do we need multivariate modeling approaches to model crash frequency by crash types? A panel mixed approach to modeling crash frequency by crash types. Anal. Methods in Accid. Res. 24, 100107.
Bhowmik, T., Yasmin, S., Eluru, N., 2021. A new econometric approach for modeling several count variables: a case study of crash frequency analysis by crash type and severity. Transp. Res. B 153, 172–203.
Chen, F., Chen, S., 2011. Injury severities of truck drivers in single- and multi-vehicle accidents on rural highways. Accid. Anal. Prev. 43 (5), 1677–1688.
Chen, F., Chen, S., 2013. Differences in injury severity of accidents on mountainous highways and non-mountainous highways. Procedia. Soc. Behav. Sci. 96, 1868–1879.
Chen, C., Zhang, G., Tian, Z., Bogus, S., Yang, Y., 2015. Hierarchical bayesian random intercept model-based cross-level interaction decomposition for truck driver injury severity investigations. Accid. Anal. Prev. 85, 186–198.
Duddu, V., Penmetsa, P., Pulugurtha, S., 2018. Modeling and comparing injury severity of at-fault and not at-fault drivers in crashes. Accid. Anal. Prev. 120, 55–63.
Eker, U., Ahmed, S., Fountas, G., Anastasopoulos, P., 2019. An exploratory investigation of public perceptions towards safety and security from the future use of flying cars in the United States. Anal. Methods in Accid. Res. 23, 100103.
Eluru, N., 2013. Evaluating alternate discrete choice frameworks for modeling ordinal discrete variables. Accid. Anal. Prev. 55, 1–11.
Eluru, N., Bhat, C.R., Hensher, D.A., 2008. A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. Accid. Anal. Prev. 40 (3), 1033–1054.
Fountas, G., Anastasopoulos, P., 2017. A random thresholds random parameters hierarchical ordered probit analysis of highway accident injury-severities. Anal. Methods in Accid. Res. 15, 1–16.
Fountas, G., Anastasopoulos, P., Abdel-Aty, M., 2018. Analysis of accident injury-severities using a correlated random parameter ordered probit approach with time variant covariates. Anal. Methods in Accid. Res. 18, 57–68.
Fountas, G., Fonzone, A., Olowosegun, A., Mctigue, C., 2021. Addressing unobserved heterogeneity in the analysis of bicycle crash injuries in scotland: a correlated random parameters ordered probit approach with heterogeneity in means. Anal. Methods in Accid. Res. 32, 100181.
Haq, M., Zlatkovic, M., Ksaibati, K., 2020a. Assessment of tire failure related crashes and injury severity on a mountainous freeway: Bayesian binary logit approach. Accid. Anal. Prev. 145, 105693.
Haq, M., Zlatkovic, M., Ksaibati, K., 2020b. Investigating occupant injury severity of truck-involved crashes based on vehicle types on a mountainous freeway: a hierarchical bayesian random intercept approach. Accid. Anal. Prev. 144, 105654.
Hosseinpour, M., Haleem, K., 2021. Examining crash injury severity and barrier-hit outcomes from cable barriers and strong-post guardrails on Alabama's interstate highways. J. Saf. Res. 78, 155–169.
Hou, Q., Huo, X., Leng, J., Cheng, Y., 2019. Examination of driver injury severity in freeway single-vehicle crashes using a mixed logit model with heterogeneity-in-means. Physica A 531, 121760.
Hou, Q., Hou, X., Leng, J., Mannering, F., 2022. A note on out-of-sample prediction, marginal effects computations, and temporal testing with random parameters crash-injury severity models. Anal. Methods in Accid. Res. 33, 100191.
Hu, W., Donnell, E., 2010. Median barrier crash severity: Some new insights. Accid. Anal. Prev. 42 (6), 1697–1704.
Huang, H., Peng, Y., Wang, J., Luo, Q., Li, X., 2018. Interactive risk analysis on crash injury severity at a mountainous freeway with tunnel groups in China. Accid. Anal. Prev. 111, 56–62.
Intini, P., Berloco, N., Fonzone, A., Fountas, G., Ranieri, V., 2020. The influence of traffic, geometric and context variables on urban crash types: A grouped random parameter multinomial logit approach. Anal. Methods in Accid. Res. 28, 100141.
Islam, M., Mannering, F., 2021. The role of gender and temporal instability in driver-injury severities in crashes caused by speeds too fast for conditions. Accid. Anal. Prev. 153, 106039.
Islam, M., Alnawmasi, N., Mannering, F., 2020. Unobserved heterogeneity and temporal instability in the analysis of work-zone crash-injury severities. Anal. Methods in Accid. Res. 28, 100130.
Islam, M., Mannering, F., 2020. A temporal analysis of driver-injury severities in crashes involving aggressive and non-aggressive driving. Anal. Methods in Accid. Res. 27, 100128.
Li, Z., Chen, C., Ci, Y., Zhang, G., Wu, Q., Liu, C., Qian, Z., 2018. Examining driver injury severity in intersection-related crashes using cluster analysis and hierarchical bayesian models. Accid. Anal. Prev. 120, 139–151.
Liu, X., Xiao, H., Liu, C., Li, Y., Xiao, H., Wang, Y., 2010. Response of stable carbon isotope in epilithic mosses to atmospheric nitrogen deposition. Environ. Pollut. 158 (6), 2273–2281.
Mannering, F., 2018. Temporal instability and the analysis of highway accident data. Anal. Methods in Accid. Res. 17, 1–13.
Mannering, F., Shankar, V., Bhat, C., 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. Anal. Methods in Accid. Res. 11, 1–16.
Mcfadden, D., Train, K., 2000. Mixed MNL models for discrete response. J. Appl. Economet. 15 (5), 447–470.
Molan, A., Ksaibati, K., 2021a. Factors impacting injury severity of crashes involving traffic barrier end treatments. Int. J. Crashworthiness 26 (2), 202–210.
Molan, A., Ksaibati, K., 2021b. Impact of side traffic barrier features on the severity of run-off-road crashes involving horizontal curves on non-interstate roads. Int. J. Transp. Sci. Technol. 10 (3), 245–253.
Molan, A., Moomen, M., Ksaibati, K., 2019. Investigating the effect of geometric dimensions of median traffic barriers on crashes: Crash analysis of interstate roads in Wyoming using actual crash datasets. J. Saf. Res. 71, 163–171.
Molan, A., Moomen, M., Ksaibati, K., 2020a. The impact of traffic barrier geometric features on crash frequency and injury severity of non-interstate highways. J. Saf. Res. 75, 155–165.
Molan, A., Moomen, M., Ksaibati, K., 2020b. Estimating the effect of geometric features of side traffic barriers on crash severity of interstate roads in Wyoming. Accid. Anal. Prev. 144, 105639.
Molan, A., Rezapour, M., Ksaibati, K., 2020c. Investigating the relationship between crash severity, traffic barrier type, and vehicle type in crashes involving traffic barrier. J. Traffic Transp. Eng. 7 (1), 125–136.
Molan, A., Rezapour, M., Ksaibati, K., 2020d. Modeling the impact of various variables on severity of crashes involving traffic barriers. J. Transp. Saf. Security 12 (6), 800–817.
National Highway Traffic Safety Administration, 2014. 2013 Motor Vehicle Crashes: Overview. Washington, DC: US Department of Transportation, National Highway Traffic Safety Administration.
Pantangi, S., Ahmed, S., Fountas, G., Majka, K., Anastasopoulos, P., 2021. Do high visibility crosswalks improve pedestrian safety? A correlated grouped random parameters approach using naturalistic driving study data. Anal. Methods Accid. Res. 30, 100155.

Park, J., Abdel-Aty, M., Lee, J., 2016. Use of empirical and full bayes before–after approaches to estimate the safety effects of roadside barriers with different crash conditions. J. Saf. Res. 58, 31–40.
Rezapour, M., Moomen, M., Ksaibati, K., 2019a. Ordered logistic models of influencing factors on crash injury severity of single and multiple-vehicle downgrade crashes: a case study in Wyoming. J. Saf. Res. 68, 107–118.
Rezapour, M., Wulff, S., Ksaibati, K., 2019b. Examination of the severity of two-lane highway traffic barrier crashes using the mixed logit model. J. Saf. Res. 70, 223–232.
Rezapour, M., Molan, A., Ksaibati, K., 2020. Analyzing injury severity of motorcycle at-fault crashes using machine learning techniques, decision tree and logistic regression models. Int. J. Transp. Sci. Technol. 9 (2), 89–99.
Rezapour, M., Wulff, S.S., Molan, A., Ksaibati, K., 2021. Application of bayesian ordinal logistic model for identification of factors to traffic barrier crashes: Considering roadway classification. Transportation Letters 13 (4), 308–314.
Russo, B., Savolainen, P., 2018. A comparison of freeway median crash frequency, severity, and barrier strike outcomes by median barrier type. Accid. Anal. Prev. 117, 216–224.
Wang, Y., Prato, C., 2019. Determinants of injury severity for truck crashes on mountain expressways in China: A case-study with a partial proportional odds model. Saf. Sci. 117, 100–107.
Waseem, M., Ahmed, A., Saeed, T., 2019. Factors affecting motorcyclists' injury severities: an empirical assessment using random parameters logit model with heterogeneity in means and variances. Accid. Anal. Prev. 123, 12–19.
Washington, S., Karlaftis, M., Mannering, F., Anastasopoulos, P., 2020. Statistical and Econometric Methods for Transportation Data Analysis. CRC Press, Taylor and Francis Group, New York, NY.
Wen, H., Xue, G., 2020. Injury severity analysis of familiar drivers and unfamiliar drivers in single-vehicle crashes on the mountainous highways. Accid. Anal. Prev. 144, 105667.
Yan, X., He, J., Wu, G., Zhang, C., Wang, C., Ye, Y., 2022. Differences of overturned and hit-traffic barrier crashes on rural roads accompanied by speeding driving: accommodating potential temporal shifts. Anal. Methods Accid. Res., 100220
Yasmin, S., Eluru, N., 2013. Evaluating alternate discrete outcome frameworks for modeling crash injury severity. Accid. Anal. Prev. 59, 506–521.
Yasmin, S., Eluru, N., Pinjari, A.R., 2015. Analyzing the continuum of fatal crashes: a generalized ordered approach. Anal. Methods Accid. Res. 7, 1–15.
Yu, R., Abdel-Aty, M., 2014a. Analyzing crash injury severity for a mountainous freeway incorporating real-time traffic and weather data. Saf. Sci. 63, 50–56.
Yu, R., Abdel-Aty, M., 2014b. Using hierarchical bayesian binary probit models to analyze crash injury severity on high speed facilities with real-time traffic data. Accid. Anal. Prev. 62, 161–167.
Yu, M., Ma, C., Shen, J., 2020a. Temporal stability of driver injury severity in single-vehicle roadway departure crashes: a random thresholds random parameters hierarchical ordered probit approach. Anal. Methods Accid. Res. 29, 100144.
Yu, R., Xiong, Y., Abdel-Aty, M., 2015. A correlated random parameter approach to investigate the effects of weather conditions on crash risk for a mountainous freeway. Transp. Res. C 50, 68–77.
Yu, M., Zheng, C., Ma, C., 2020b. Analysis of injury severity of rear-end crashes in work zones: a random parameters approach with heterogeneity in means and variances. Anal. Methods Accid. Res. 27, 100126.
Yu, M., Zheng, C., Ma, C., Shen, J., 2020c. The temporal stability of factors affecting driver injury severity in run-off-road crashes: a random parameters ordered probit model with heterogeneity in the means approach. Accid. Anal. Prev. 144, 105677.
Zou, Y., Tarko, A., Chen, E., Romero, M., 2014. Effectiveness of cable barriers, guardrails, and concrete barrier walls in reducing the risk of injury. Accid. Anal. Prev. 72, 55–65.