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Contents lists available at ScienceDirect

# International Journal of Transportation Science and Technology

journal homepage: www.elsevier.com/locate/ijtst



# Bicyclist injury severity classification using a random parameter logit model

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#### ARTICLE INFO

#### Article history: Received 27 August 2022 Received in revised form 22 January 2023 Accepted 3 February 2023 Available online xxxx

Keywords:
Bicyclist crash
Safety
Mixed logit model
Random parameter model
Unobserved heterogeneity

## ABSTRACT

Bicycling has been actively promoted as a clean and efficient mode of commute. Besides, due to the personal and societal benefits it provides, it has been adopted by many city dwellers for short-distance trips. Despite the integral role this active transport mode plays, it is unfortunately associated with a high risk of fatalities in the event of a traffic crash as they are not protected. Many studies have been conducted in several jurisdictions to examine the factors contributing to crashes involving these vulnerable road users. In the case of Louisiana which is currently experiencing increased cases of severe and fatal bicycleinvolved crashes, less attention has been paid to investigating the critical factors influencing bicyclist injury severity outcomes using more detailed data and advanced econometric modeling frameworks to help propose adequate policies to improve the safety of riders. Against this background, this study examined the key contributing factors influencing bicyclist injuries by using more detailed roadway crash data spanning 2010-2016 obtained from the state of Louisiana. The study then applies an advanced random parameter logit modeling with heterogeneity in means and variances to address the unobserved heterogeneity issue associated with traffic crash data. To overcome the imbalanced data issue, three major crash injury levels were used instead of the conventional five crash injury levels. Besides, the data groups classified under each injury level were compared for the final variable selection. The study found that distracted drivers, elderly bicyclists, careless operations, and riding in dark conditions increase the probability of having severe injuries in vehicle-bicyclist crashes. Moreover, the variables for straight-level roadways and city streets decrease the odds of severe injuries. The straight-level roadway may provide better sight distance for both drivers and bicyclists, and complex environments like city streets discourage crashes with severe injuries.

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Peer review under responsibility of Tongji University and Tongji University Press.

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# https://doi.org/10.1016/j.ijtst.2023.02.001

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Please cite this article as: S. Das, R. Tamakloe, H. Zubaidi et al., Bicyclist injury severity classification using a random parameter logit model, International Journal of Transportation Science and Technology, https://doi.org/10.1016/j.ijtst.2023.02.001

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## 1. Introduction

Besides being used as a recreational transport mode, cycling is a low-cost, healthy, and environmentally friendly travel mode for short-duration trips. Generally, city planners and decision-makers expect to increase the number of bicycle riders to enhance the overall livability of the city or urban center. Although bicycling has become one of the major transportation modes in urban areas and city centers, inept transportation planning causes non-motorized road users such as bicyclists to face major safety concerns. According to the National Highway Traffic Safety Administration (NHTSA), over a 10-year period (2009 to 2018), bicyclist fatalities have increased by 37 % (NHTSA, 2020). Besides, over from 2010 to 2016, bicyclist crashes increased by 21 %, and bicyclist fatalities increased by 91 % in Louisiana. These statistics indicate that achieving the long-term goal of making livable city centers by increasing the number of bicyclists requires conducting more comprehensive studies to identify factors influencing bicycle safety and ensuring the safety of these vulnerable roadway users.

Researchers applied many methods to assess bicyclist crash risks by determining the impact of key contributing factors. However, these methods were mainly traditional statistical models (e.g., fixed-parameters or fixed-effects models), which are often not robust in addressing the heterogeneity problem of police-reported crash datasets. This constraint can lead to biased predictors and inaccurate explanations of the model outcomes, resulting in countermeasures that are not suitable for addressing the issues. Further, majority of the studies did not employ comprehensive data containing key variables in their models. This study aims to fill the research gap by exploring the true impact of key contributing factors on bicyclist crash risks with the application of a robust statistical method. This study collected seven years (2010–2016) of traffic crash data with crash, driver, bicyclist, and roadway inventory information from Louisiana to perform the analysis. First, key contributing factors are selected, and the difference between the proportion distributions of these variable attributes by crash injury types was determined for the final variable selection. Second, this study applied a mixed logit model on the collected dataset to estimate the impact of the variable attributes on bicyclist injury type.

This study has two major contributions. First, the paper developed vehicle-bicycle crash severity modeling to address bicycle-related traffic safety concerns in Louisiana, which has experienced a sharp jump in bicyclist crashes in recent years. The complexity of the crash dataset and unobserved heterogeneity due to the missing variable issues were addressed using an advanced econometric modeling technique. Second, more comprehensive data relating to the highway type, bicycle movement, roadway alignment, traffic control, lighting condition, bicyclist features, weather condition, driver attributes were explored, and the modeling results in terms of explainability of the final variables were explained in-depth. The results and discussions can provide some implications for policies and countermeasures to improve bicyclist safety. Besides, the findings of the study can shed some light on the effects of the key contributing factors on the injury severities of vehicle-bicycle crashes.

#### 2. Literature review

Despite the usefulness of bicycles, they are known to be associated with high injury severity outcomes as the riders are not protected, as in the case of vehicle occupants. To make riding safe and encourage cycling, researchers have focused on analyzing the factors affecting injury severity outcomes of bicycle-involved crashes. As the factors influencing crash outcome metrics are spatially unstable (Ahmed et al., 2023; Tamakloe and Park, 2022), some factors may likely have different effects on injury severity outcomes in different jurisdictions. Thus, researchers tend to analyze crash data from different locations separately in order to propose policies that can be beneficial in solving the traffic safety problem at hand. In a study from Great Britain, analysis results showed that the risk of sustaining fatal/severe injuries rises with increases in cyclists' age and road speed limits. Besides, truck involvement was found to be a key factor associated with fatal severity outcomes (Mason-Jones et al., 2022). Using data from Los Angeles, rear-end collisions and early morning crashes were identified to be associated with increases in the chances of observing severe bicyclist injuries (Hosseini et al., 2022). Another study from Nashville and Memphis noted that weekends and inadequate lighting conditions were critical factors that affect bike crash severity outcomes (Dash et al., 2022). A study aimed at exploring influence factors on injury severity of bicycle-involved collisions in Beijing also identified heavy vehicle involvement as a crucial determinant of fatalities in urban areas (Sun et al., 2022). Other studies from Australia, North Carolina (USA), and Aarhus (Denmark) revealed that not riding on bicycle lanes, bad weather, alcohol involvement, and wet road surfaces (Lin and Fan, 2021; Myhrmann et al., 2021; Samerei et al., 2021).

Regarding methodologies, many bicycle-involved crash studies applied logit models to explore the key factors affecting injury severity outcomes. Klop and Khattak (1999) developed an ordered probit model to detect influencing factors to bicycle crash severity on two-lane, undivided roadways. Kim et al. (2007) applied a multinomial logit modeling technique to analyze the determinants of the severity of bicyclists' injuries in vehicle-bicycle crashes. Yan et al. (2011) and Bahrololoom et al. (2016) developed binary logit models to investigate the relationships between irregular maneuvers, crash patterns, and bicyclist injury type. Boufous et al. (2012) developed a logistic regression model to investigate the injury severity of bicycle crashes in Victoria, Australia. Some of the key contributing factors identified in this study are 50 years and older bicyclists, curved roadway sections, unlighted dark conditions, not wearing a helmet, rural locations, curved roadway sections, speeding, and run-off-road crashes. The same database was used by Boufous et al. (2013) to compare single- and multi-vehicle bicycle crashes patterns. The results showed that rural areas, wet surfaces, and dark lighting conditions are associated with higher risk. Robartes and Chen (2017) developed an ordered probit model to explore key factors affecting the severity of

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single bicycle-single-vehicle crashes. Environmental traits, roadway characteristics, and vehicle, driver, and bicyclist characteristics were considered for analysis. Robartes and Chen (2017) focused on single-bicycle-vehicle related crashes and used a wide range of variables to develop an order probit model – impairment of bicyclists and drivers, vertical and horizontal grades, and vehicle and bicycle speeds were found to be key contributing factors.

To address heterogeneity issues, econometric modeling frameworks were applied to some studies. Bahrololoom et al. (2018) used a random parameter binary logit model to study the effect of factors impacting bicycle crash severity related to the safe system approach. Moore et al. (2011) determined that bicyclist injury severity levels differ in patterns in the intersection and non-intersection-related crashes by using crash data from Ohio between 2002 and 2008. Kaplan et al. (2014) and Bahrololoom et al. (2017) studied the determinants of bicyclist injury level using a generalized order probit model and a generalized order logit model, respectively. Helak et al. (2017) developed univariate and multiple regression models to assess how the injury severity of bicyclists was impacted by helmet usage, speeding, impairment, lighting condition, and the presence of bike lanes. Yasmin and Eluru (2018) developed a joint negative binomial-ordered logit fractional split econometric model framework to analyze the total crash count and crash proportion by various crash severity levels. More recent studies from North Carolina, China, and Los Angeles also applied mixed logit models to analyze bicycle-involved crash data (Hosseini et al., 2022; Lin and Fan, 2021; Sun et al., 2022). It is noteworthy that although the majority of the studies applied the traditional random parameter or mixed logit models for their analyses. These methods can deal with unobserved heterogeneity issues to some extent. However, they have a number of drawbacks in terms of adequately capturing unobserved heterogeneity in crash data, which makes them less desirable by safety experts (Obaid et al., 2022). To properly address the problem of unobserved heterogeneity, Behnood and Mannering (2017a) developed a random parameter multinomial logit model with heterogeneity in means and variance using data from Los Angeles to explore factors influencing bicycle-involved crash injury severity outcomes. The results showed a significant model fit compared to the traditional mixed logit model.

Latent clustering and spatial heterogeneity issues in vehicle-bicycle crash datasets were explored in some studies. Sivasankaran and Balasubramanian (2020) used logistic regression to examine variables that could affect bicyclist injury severity, and they applied the latent class clustering (LCC) technique to solve the heterogeneity issues. To account for spatial heterogeneity, Liu et al. (2020) proposed the geographically weighted ordinal logistic regression model by presenting that crash injury level is increased by the operating speed of vehicles and bicyclists, ride age and behavior, and impairment. Similar approaches which involve the use of regression models after segregating the data into homogeneous clusters have also been adopted and used in more recent years (Chen and Mei, 2021; Samerei et al., 2021; Sun et al., 2021).

Some studies developed crash severity modeling of bicycle crashes on certain types of infrastructure such as intersections (Asgarzadeh et al., 2017; Bahrololoom et al., 2018a, 2018b), both intersections and mid-blocks (Klassen et al., 2014), the influence of sharrow (Wall et al., 2016), unsignalized intersection (Wang et al., 2015), urban intersections (Stipancic et al., 2016), and effects of various traffic control types at the intersection (Rash-ha Wahi et al., 2018). In particular, it has been shown that, while variables such as speeding, curved road, alcohol involvement, and traffic control presence are significant determinants of fatality at non-intersections, heavy vehicles (bus and trucks), inclement weather, and dawn/dusk conditions have a significant influence on cyclist injury severity outcomes at intersection areas (Lin and Fan, 2021).

Due to the high number of severe injuries (SI) associated with bicyclists, city planners started to focus more on ensuring safer mobility for bicyclists. Most studies concerning the relationship between bicycle crash injury severity and other influencing factors have applied fixed effect modeling for their analyses, which has led to key research gaps. First, bicyclist crash severity studies from Louisiana are scanty despite the high severity outcomes of crashes recorded yearly. Secondly, not many studies were dedicated to using advanced crash severity modeling tools for vehicle-bicycle crashes compared to vehicle-vehicle crashes. Finally, there is limited knowledge of the influence of key factors such as roadway geometry, street, crash, environmental, and bicyclist-related parameters on bicyclist injury severity outcomes. This paper aims to contribute to the literature by determining significant factors that contribute to the severity of vehicle-bicycle crashes by addressing these research gaps. Using comprehensive data obtained from Louisiana, a robust econometric model that deals with unobserved heterogeneity at several levels is developed to improve model fit and reduce estimation bias. This study is expected to lead to the identification of key policies for improving the safety of cyclists in Louisiana.

The paper is organized as follows. First, an introduction is provided to elaborate on the importance of studying cycling safety and identify the research gap. Second, the description of the data used for this study is presented, and the methodology section follows by introducing the mathematical theory of the technique used for the analysis. A result section follows the methodology section and concludes with a summary of the key findings identified from the analysis. A conclusion section is presented at the end of the paper.

## 3. Data description

This study collected traffic crash data from Louisiana for seven years (2010–2016), which includes crash, vehicle, and roadway-related information. The final data set contains details from 6,136 crashes between bicycles and motor vehicles. Note that each crash may involve multiple vehicles and multiple drivers or bicyclists. Unique crash numbers are used in the analysis, and this unique identification is selected based on the maximum injury among all injuries. For example, if a crash involves one driver and one bicyclist, a single crash will have two entries, and the entry with the maximum severity was used as the unique crash number. For most cases, the maximum injury is associated with the bicyclist, which is obvious.

The distribution of bicyclist injury severity is comprised of 132 fatal crashes (K), 258 incapacitating or severe crashes (A), 1887 non-incapacitating or moderate crashes (B), 2562 complaint crashes (C), and 1297 no injury or property damage only or PDO (O) crashes. Fig. 1 shows the counts across all severity categories from 2010 to 2016. For each category, the general trend of the counts of crashes involving bicyclists increases across the years, except for the K and A categories. For the K category, the count spiked in 2012 and dropped to about half in the following two years. Then the fatal crashes spiked again in 2015 and dropped significantly in 2016 again. For the C category, from 2010 to 2016, most years have counts between 30 to 40, except 2012.

Due to the relatively small number of fatal bicyclist crashes, incapacitating and fatal injuries are aggregated into a single 'severe injury' outcome category. Similarly, non-incapacitating injury and minor injury are aggregated to a single 'minor injury.' It can be noticed that the minor injuries (MI) have the highest number of crash observations – 4,449 (73 %), followed by the no injury (NI) types with 1,297 (21 %) crash observations and lastly, the SI with 390 (6 %) crash observations. Fig. 2 provides the proportion distribution of the key attributes by crash injury types.

Fig. 3 plots the crash frequency across the temporal and spatial dimensions. The hexagon on the right-hand side (where New Orleans is located) is the hottest spot across years. In seven years, multiple locations have a higher frequency than the rest. These locations are the big cities in Louisiana, wherewith many bicyclists. Another observation is that there are fewer hot spots in earlier years, such as 2010. The number of hot spots increases every year, as well as the crash frequency.

Fig. 4 shows the heatmaps of vehicle-bicycle crashes with various severities. For minor crashes, big cities are the most concentrated places. For severe injuries, the hot spots across different cities are not as obvious as compared to the case of the minor crashes.

A detailed description of the entire crash data is summarized in Table A1 in the appendix. The data comprise comprehensive information regarding variables pertaining to the driver's condition, bicyclist features, driver's violations leading to the crash, roadway type, geometric features, lighting condition, and weather characteristics.

The dataset shows that most fatal crashes involved bicyclists identified as Caucasians (50.5 %), followed by African Americans (44.4 %). The age distributions are relatively similar among the injury types, except unknown ages in the no injury group are significantly higher in counts than the other two injury levels. Besides, the data showed that older riders (50-59yrs) formed the group largely involved in severe vehicle-bicycle crashes (24.4%). The number of male bicyclists was comparatively higher than the other gender groups in the vehicle-bicycle crashes. This is a common pattern; however, exposure of male and female bicyclists is unknown in Louisiana. According to the NHTSA, 'the bicyclist fatality rate per million people was seven times higher for males than females, and the bicyclist injury rate per million people was five times higher for males than for females in 2018' (NHTSA, 2020). As expected, motor vehicles in transport show higher proportions in all three injury levels, with the highest in the severe injury group. Rear-end crashes show a higher proportion among different collision types in the severe injury group. Among highway types, city streets show a higher proportion in the 'no injury' group, and state highways are the roadways with a higher proportion in the 'severe' injury group. This can be related to the environment and posted speed limit difference between these facilities. City streets mostly have low posted speed, and vehiclebicycle collisions are mostly non-trivial due to the lower impact speed. In posted speed limit variables, low posted speed (30 mph or less) is associated with a high number of 'no injury' crashes. The dark condition shows a higher proportion of 'severe' injury crashes. It is an obvious outcome as low lighting condition makes the bicyclists vulnerable due to misjudgment of the moving vehicle drivers due to low visibility.

A summary of variables identified as significant in the models is presented in Table 1. Three main observations from the summary are as follows: first, approximately 94 percent of vehicle-bicycle crashes occurred on roadways with straight-level alignment. This is likely due to the nature of the roadway alignment in Louisiana, which is rather flat. Second, around 78 % of

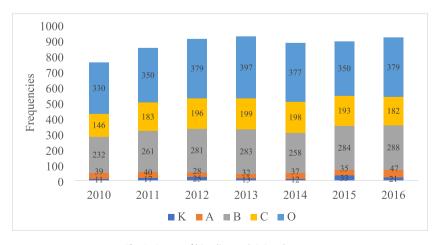


Fig. 1. Counts of bicyclist crash injury by year.

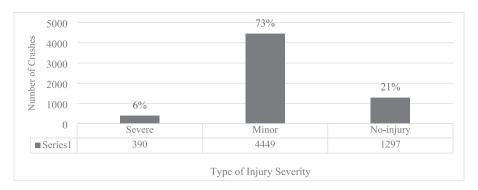


Fig. 2. Bicyclist injury severity type.

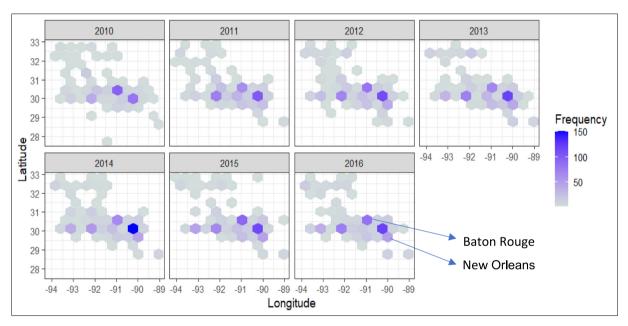


Fig. 3. Heatmap of hexagons showing bicyclist crashes by years and locations.

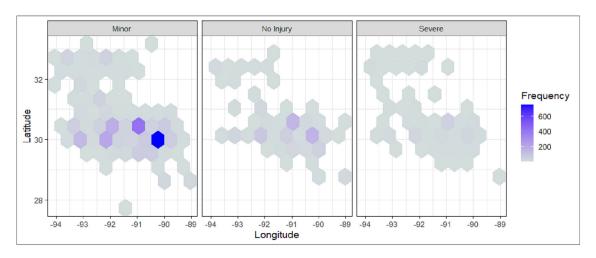


Fig. 4. Heatmap of hexagons showing bicyclist crashes by injury levels and locations.

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Descriptive statistics of the significant variables.

Variable	Categories description	Mean	Standard Deviation
Alignment	Straight level	0.947034	0.223972
Bicycle movement	Normal movement	0.396838	0.489255
Collision type	Head-on	0.02852	0.166458
	Making left turn	0.069915	0.255011
	Rear end	0.088494	0.28402
Bicyclist age	≤19 yrs.	0.23354	0.423094
	20-34 yrs	0.272653	0.445336
	35-49 yrs.	0.160039	0.366652
	50–59 yrs.	0.063396	0.243681
	≥ 60 yrs.	0.075619	0.264395
Driver condition	Distracted	0.336864	0.472651
Bicyclist gender	Male	0.775913	0.416991
Bicyclist race	African American	0.428292	0.494845
	Others	0.106747	0.3088
	Caucasian	0.464961	0.498784
Harm event	Motor vehicle in transport	0.789439	0.407718
Highway type	City street	0.564374	0.495852
	State highway	0.190189	0.392461
Light condition	Dark streetlight at intersection	0.033898	0.180972
	Dark with continuous streetlight	0.167862	0.373754
Location type	Business, industrial, manufacturing	0.655476	0.475226
Posted speed limit	≤ 30 mph	0.513038	0.499844
-	50–60 mph	0.632142	0.547633
Prior movement	Entering or leaving	0.079857	0.271078
Traffic control	No control	0.281128	0.449562
	Stop sign	0.143416	0.350506
	Yellow dashed line	0.054759	0.227515
Violation	Careless operation	0.069589	0.254461
Weather condition	Rain	0.039113	0.19387

the crashes are associated with males, which is generally reflective of the gender representation among the bicyclist population. Third, most of the crashes (around 78 %) are associated with harmful events as 'motor vehicle in transport.' It indicates that the communication difference between the moving vehicles and bicyclists is the major reason for many of these crashes.

## 4. Methodology

During the last 20 years, there has been a significant advancement in econometrics, especially econometrics methods that can resolve the unobserved heterogeneity issue characteristic of police-reported crash datasets. These advanced models can provide more rational insight into factors contributing to highway safety-related issues in the transportation safety domain. This study examined the crash injury types of bicyclists by detecting the key contributing factors that lead to specific injury types. This work performs model comparisons and justify the use of random parameter logit models over fixed-effects models with the available data. First Multinomial logit model (MNL) has been developed and then estimated a set of mixed (random parameters) that address the prevailing constraints of the multinomial logit structure with the likelihood of specific injury type based on data collected from Louisiana with 6,136 observations. The application of the mixed logit model (MXL) has several good advantages such as flexibility, explainability, and allocation of parameter randomness in an independent variable by relaxing the independence of irrelevant alternatives (Moore et al., 2011a; Haleem and Gan, 2013; Wu et al., 2014; Behnood and Mannering, 2017a, 2017b; Seraneeprakarn et al., 2017). Many studies demonstrated that MXL can assess any discrete outcome model (Moore et al., 2011b; Haleem and Gan, 2013; Wu et al., 2014; Behnood and Mannering, 2017a, 2017b; Seraneeprakarn et al., 2017, Zubaidi et al., 2022, 2021). As mentioned earlier, the injury levels (severe, minor, and no injury) are considered in this analysis. To start forming an MXL, Eq. (1) is described as:

$$S_{kn} = \beta_k X_{kn} + \varepsilon_{kn}$$
 (1)

where  $S_{kn}$  defines the utility of driver injury severity level k in crash n. Consider  $\beta_k$  a vector of estimable parameters,  $X_{kn}$  a vector of dependent features influencing crash injury k, and  $\varepsilon_{kn}$  the error term is considered independent and identically distributed (Washington et al., 2011). Also, the unobserved heterogeneity across crash observations is considered by letting  $\beta_k$ be a vector of estimable parameters which can vary across crash observations, as specified in Eq. (2) (Mannering, Shankar, and Bhat, 2016).

$$\beta_k = b + \Theta Z_k + \varphi_k \tag{2}$$

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Where b is the mean parameter approximate for all interpretations,  $Z_k$  is a vector of dependent features from crash n,  $\Theta$  is a vector of estimable parameters, and  $\varphi_k$  is a randomly distributed term that portrays unobserved heterogeneity throughout the observations. Unobserved heterogeneity in the means and variances of random parameters, as shown in Eq.3, is accounted by  $\beta_{kn}$  be a vector of estimable parameters (Seraneeprakarn et al., 2017; Behnood and Mannering, 2019).

$$\beta_{kn} = \beta + \Theta_{kn} Z_{kn} + \sigma_{kn} EXP(\omega_{kn} W_{kn}) v_{kn} \tag{3}$$

where  $\beta$  is previously defined as b,  $Z_{kn}$  is a vector of dependent features that depict the heterogeneity in the mean that influences injury outcome k,  $\Theta_{kn}$  is a consistent vector of estimable parameters,  $W_{kn}$  is a vector of crash-specific descriptive features that describes the heterogeneity in the standard deviation  $\sigma_{kn}$  with comparing parameter vector  $\omega_{kn}$ , and the disturbance term is  $v_{kn}$ .

The possibility of injury severity outcome k in crash n,  $p_n(k)$ , can be described by allowing the vector  $\beta_{kn}$  with a constant density function so that: Prob  $(\beta_{kn} = \beta) = f(\beta|\varphi)$  (Behnood and Mannering, 2017a, 2017b; Seraneeprakarn et al., 2017):

$$p_n(\mathbf{k}) = \int \frac{EXP(\beta_k X_{kn})}{\sum_{\forall l} EXP(\beta_k X_{kn})} f(\beta|\varphi) \, \mathrm{d}\beta \tag{4}$$

where  $p_n(k)$  is the likelihood of injury severity outcome k in crash n.

Model evaluation was supported by simulated maximum likelihood with 1,000 Halton draws (McFadden and Train, 2000). After considering several distributions, normal distribution was selected due to its best measurable fit in this study. This study also provided measures of marginal effects, which provide additional insight into the estimated results.

## 5. Results and discussions

Prior to analyzing the crash data, preliminary tests were performed in R (version 3.6.0) using the package 'compareGroups' (Salvador, 2021) to verify if the data groups classified based on the injury levels are equal or not. Upon running Chi-square

Table 2
Multinomial logit model outcomes.

Variables	Categories description	Coefficient	t-stat	p-value
Constant	[SI]	-1.272	-5.31	0.000
	[MI]	-0.196	-1.60	0.109
Driver condition	distracted [SI]	-0.781	-5.63	0.000
Bicyclist race	race O [SI]	-0.756	-3.11	0.002
	race W [MI]	0.957	11.92	0.000
	race B [NI]	-1.266	-13.57	0.000
Bicycle movement	normal movement [SI]	-0.624	-4.78	0.000
Prior movement	entering or leaving [SI]	0.725	4.07	0.000
Traffic control	stop sign [SI]	0.472	2.93	0.003
	yellow dashed line [SI]	0.668	3.46	0.001
	no control [NI]	0.134	1.86	0.064
Alignment	straight level [SI]	-0.777	-4.18	0.000
Posted speed limit	50-60 mph [SI]	0.567	3.08	0.002
	≤ 30 mph [NI]	0.1969	2.82	0.005
Light condition	dark with continuous streetlight [SI]	0.325	2.33	0.019
	dark streetlight at intersection [SI]	0.678	2.96	0.003
Collision type	head-on [SI]	0.834	3.37	0.001
	rear end [SI]	1.234	8.26	0.000
	making left turn [MI]	0.222	1.79	0.073
Bicyclist age	50-59 yrs. [SI]	0.365	2.70	0.007
	20-34 yrs. [MI]	0.183	-1.60 -5.63 -3.11 11.92 -13.57 -4.78 4.07 2.93 3.46 1.86 -4.18 3.08 2.82 2.33 2.96 3.37 8.26 1.79	0.012
	≤19 yrs. [NI]	-0.301		0.001
	≥ 60 yrs. [SI]	0.329		0.083
Highway type	state highway [MI]	0.228	2.73	0.006
	city street [SI]	-0.554	-4.49	0.000
Weather condition	rain [MI]	0.3301	2.03	0.042
Driver gender	male [NI]	-0.512	-6.75	0.000
Violation	careless operation [SI]	-0.636	-2.47	0.013
Harm event	motor vehicle in transport [NI]	-0.279	-3.67	0.000
Location type	business, industrial, manufacturing [NI]	0.196	2.68	0.007
Model Statistics				
Log-likelihood at convergence		-4132.260		
Log-likelihood with consta	nts only	-4520.773		
McFadden Pseudo R-square	ed	0.084		
AIC		8324.5		
No. of observation		6136		

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tests, the p-value results were obtained and provided in Table A1. The p-value measures for each variable are less than 0.05, indicating that the variables statistically differ between the three injury groups. The outcomes of applying basic regression model are presented in Table 2. Upon verifying that the variables differ between the three injury groups, the MXL model was employed for detailed analysis. The variable coefficient estimates, and the computed marginal effect estimates obtained from the MXL model are presented in Table 3. The results are explained according to the various crash injury severity levels for which the crash-risk factors were defined. From the model statistics for both models, it can be notices that the Log-likelihood at convergence values are -4132.260 and -3935.98 for MNL and MXL models respectively. McFadden Pseudo R-squared was found to be 0.084 in MNL and 0.4161 in MXL. Regarding the AIC the result outcome indicated that in MNL is 8324.5 and in MXL is 7986. From the above comparison it can be concluded that random parameters tend to provide added advantages over the basic regression models in explaining the significant variables therefore, it was adopted in the current research.

## 5.1. Severe injury

Driver condition (1 if distracted, 0 otherwise) was found to be a significant normally distributed random parameter variable, as shown in Table 3. The distribution parameters are estimated to have a mean measure of -9.32423 and a standard deviation of 7.86817 for severe injury, which indicates that around 88.2 % of this normal distribution is lower than zero and 11.8 % of the distribution is above zero. This infers that the possibility of severe injury rises by 11.8 % if the driver is distracted. The reaction time to an emergency could be significantly increased when the driver is distracted, which could lead to severe injuries if a vulnerable road user, such as a bicyclist, is involved. This finding echoes the results found in Lym and Chen (2021), which is that distracted driving is associated with more severe injuries.

The movement of the bicyclist (1 if normal movement, 0 otherwise) defined for severe injury or SI category produced a normally distributed random parameter with a mean of -6.14264 and a standard deviation of 4.84277. The marginal effect estimate (ME = -0.0076) indicates a reduction in the probability of severe injuries when the bicycle movement is normal. Besides, the distribution for the random parameter showed an increased probability of severe injuries for 10.23% of bicyclists' normal movement-involved crashes and decreased probability of severe injuries for the remaining crashes. The increase in the probability of the 10.23% of normal bicycle movements is substantial and might be indicative of insufficient bicycle accommodation facilities and protection for bicyclists.

Further, it is interesting to note that entering or leaving maneouvers made by bicyclists prior to the crash (defined for the severe injury category) were likely to cause severe injuries. As shown in Table 3, the marginal effect estimates were found to increase the probability of severe injury by 0.0038 and decrease the probability of minor and no injuries by -0.0031 and -0.0006, respectively. Entering maneouvers can be particularly dangerous, especially at intersections. Whereas the study conducted by Shen et al. (2020) identified that entering maneuvers at crossroads and T-junctions increased the propensity of fatal and serious injury categories, Asgarzadeh et al. (2017) established that vehicle-bicycle crashes at non-orthogonal intersections are likely to have fatal outcomes. The authors alluded to the fact that both drivers and riders experience a delay in reaction time as they have a short time to prepare as they enter an intersection. This highlights the need to reduce traffic speeds on approaching or on preparing to enter an intersection.

As shown in Table 3, the variable for traffic control (1 if stop sign, 0 otherwise) generates random parameters with a mean of 0.72046 and a standard deviation of 5.01378. The marginal effects estimate (ME = 0.0047) shows an increase in the probability for observing severe injuries in vehicle-bicycle crashes at locations with stop sign present. From the distributions of the random parameter, it is evident that there is a decreased possibility of severe injuries for 44.29 % of the observations and an increased possibility of severe injuries for 55.71 % of the observations. Besides, the traffic control type characterized by a yellow dashed line sign was identified to increase the probability of sustaining severe injuries (ME = 0.0041) and reduced the possibilities of minor (ME = -0.0035) and no injuries (ME = -0.0006). The finding that traffic controls increase the likelihood of severe injuries is consistent with the literature. According to Wahi et al. (2018), bicyclists were likely to sustain severe injuries when a vehicle-bicycle crash occurs at a segment with a give way or stop sign. Besides, Jaber et al. (2021) also noted that the probability of being severely injured is high when traffic signals are present. The vulnerability of bicyclists is likely to increase at signalized segments due to the high traffic volumes in those areas. In addition, drivers failing to yield to bicyclists at stop-controlled segments are likely to result in catastrophic consequences.

Riding on straight roads is less likely to be associated with severe bicyclist injury severity in the event of a crash (ME = -0.0143). The alignment variable (1 if straight level, 0 otherwise) defined for severe injury outcome produced a random parameter that is normally distributed with a mean of -7.46855 and a standard deviation of 5.39469. This indicates that for 8.31 % of the observations, straight level roadways increase the probability of severe injuries, and for 91.69 % of the observation, straight level roadways decreased the probability of severe injuries outcome. The result shows that, for most bike-related crashes, the odds of severe injuries are low when the crash occurs on a straight-level roadway. Bicyclists are more likely to be noticed by drivers on the straight-level roadway. Besides, unlike curved or crest alignments, both the rider and driver enjoy the benefit of sufficient sight distance, which helps them avoid potential conflicts leading to severe crashes (Rash-ha Wahi et al., 2018). This might be why the straight and leveled roadways are associated with decreasing probability of having severe injuries.

**Table 3**Mixed logit model with heterogeneity in mean and variance of the random parameters.

Severe Injury  Constant [SI] -2.2: Driver condition (1 if distracted, 0 otherwise) [SI] -9.3: Standard Deviation of Parameter, Normally Distributed 7.868 Bicycle movement (1 if normal movement, 0 otherwise) [SI] -6.1: Standard Deviation of Parameter, Normally Distributed 4.842 Traffic control (1 if stop sign, 0 otherwise) [SI] 0.720 Standard Deviation of Parameter, Normally Distributed 5.014 Alignment (1 if straight level, 0 otherwise) [SI] -7.4 Standard Deviation of Parameter, Normally Distributed 5.395 Posted speed limit (1 if between 50-60 mph, 0 otherwise) [SI] 0.121 Standard Deviation of Parameter, Normally Distributed 5.395 Highway type (1 if city street, 0 otherwise) [SI] -19. Standard Deviation of Parameter, Normally Distributed 16.66 Bicyclist race (1 if race 0, 0 otherwise) [SI] -6.88 Bicyclist age (1 if age [50-59 yrs.], 0 otherwise) [SI] 1.321 Bicyclist age (1 if age ≥ 60 yrs.), 0 otherwise) [SI] 2.958 Traffic control (1 if yellow dashed line, 0 otherwise) [SI] -2.8 Light condition (1 if dark with continuous streetlight, 0 otherwise) [SI] 1.794	324 68 143 42 20 114 469 95 21 28 9.576 602 8802 21 68 58	-3.28 -3.60 3.78 -3.44 3.29 0.36 1.65 -4.92 4.02 0.08 2.20 -3.37 3.85 -4.07 2.29 1.77 4.37	0.001 0.000 0.000 0.000 0.001 0.708 0.073 0.000 0.625 0.018 0.001 0.000 0.000 0.000	0.0006 -0.00470.0143 - 0.0034 - 0.0166 0.0037 0.0030	Minor injury (MI)  - 0.0006  0.0066 0.0038 - 0.0128 0.0027 0.0127 - 0.0016	No Injury (NI  - 0.0001  0.0011 0.0008 - 0.0015 0.0007 0.0038
Constant [SI] — 2.22 Driver condition (1 if distracted, 0 otherwise) [SI] — 9.33 Standard Deviation of Parameter, Normally Distributed 7.866 Bicycle movement (1 if normal movement, 0 otherwise) [SI] — 6.854 Standard Deviation of Parameter, Normally Distributed 4.845 Traffic control (1 if stop sign, 0 otherwise) [SI] 0.720 Standard Deviation of Parameter, Normally Distributed 5.014 Alignment (1 if straight level, 0 otherwise) [SI] — 7.45 Standard Deviation of Parameter, Normally Distributed 5.395 Posted speed limit (1 if between 50–60 mph, 0 otherwise) [SI] 0.125 Standard Deviation of Parameter, Normally Distributed 5.425 Highway type (1 if city street, 0 otherwise) [SI] — 19. Standard Deviation of Parameter, Normally Distributed 16.60 Bicyclist race (1 if race 0, 0 otherwise) [SI] — 6.88 Bicyclist age (1 if age [50–59 yrs.], 0 otherwise) [SI] 1.321 Bicyclist age (1 if age $\geq$ 60 yrs.), 0 otherwise) [SI] 1.321 Prior movement (1 if entering or leaving, 0 otherwise) [SI] 2.955 Traffic control (1 if yellow dashed line, 0 otherwise) [SI] 3.154 Violation (1 if careless operation, 0 otherwise) [SI] -2.88	324 68 143 42 20 114 469 95 21 28 9.576 602 8802 21 68 58	-3.60 3.78 -3.44 3.29 0.36 1.65 -4.92 4.02 0.08 2.20 -3.37 3.85 -4.07 2.29 1.77	0.000 0.000 0.000 0.001 0.708 0.073 0.000 0.625 0.018 0.001 0.000 0.000 0.000	-0.0076 - 0.0047 - -0.0143 - 0.0034 - 0.0166 - -0.0037	0.0066 - -0.0038 - 0.0128 - -0.0027 - -0.0127	0.0011 - -0.0008 - 0.0015 - -0.0007 - -0.0038
Driver condition (1 if distracted, 0 otherwise) [SI] $-9.3$ . Standard Deviation of Parameter, Normally Distributed $7.868$ Bicycle movement (1 if normal movement, 0 otherwise) [SI] $-6.1$ . Standard Deviation of Parameter, Normally Distributed $4.845$ . Traffic control (1 if stop sign, 0 otherwise) [SI] $0.72$ 0 Standard Deviation of Parameter, Normally Distributed $4.845$ 0.014 Alignment (1 if straight level, 0 otherwise) [SI] $0.72$ 0 Standard Deviation of Parameter, Normally Distributed $0.72$ 1 Standard Deviation of Parameter, Normally Distributed $0.72$ 2 Standard Deviation of Parameter, Normally Distributed $0.72$ 3 Standard Deviation of Parameter, Normally Distributed $0.72$	324 68 143 42 20 114 469 95 21 28 9.576 602 8802 21 68 58	-3.60 3.78 -3.44 3.29 0.36 1.65 -4.92 4.02 0.08 2.20 -3.37 3.85 -4.07 2.29 1.77	0.000 0.000 0.000 0.001 0.708 0.073 0.000 0.625 0.018 0.001 0.000 0.000 0.000	-0.0076 - 0.0047 - -0.0143 - 0.0034 - 0.0166 - -0.0037	0.0066 - -0.0038 - 0.0128 - -0.0027 - -0.0127	0.0011 - -0.0008 - 0.0015 - -0.0007 - -0.0038
Standard Deviation of Parameter, Normally Distributed7.868Bicycle movement (1 if normal movement, 0 otherwise) [SI]−6.1-Standard Deviation of Parameter, Normally Distributed4.842Traffic control (1 if stop sign, 0 otherwise) [SI]0.720Standard Deviation of Parameter, Normally Distributed5.014Alignment (1 if straight level, 0 otherwise) [SI]−7.4-Standard Deviation of Parameter, Normally Distributed5.395Posted speed limit (1 if between 50–60 mph, 0 otherwise) [SI]0.121Standard Deviation of Parameter, Normally Distributed5.428Highway type (1 if city street, 0 otherwise) [SI]−19.Standard Deviation of Parameter, Normally Distributed16.60Bicyclist race (1 if race 0, 0 otherwise) [SI]−6.81Bicyclist age (1 if age $\geq$ 60 yrs.), 0 otherwise) [SI]1.356Prior movement (1 if entering or leaving, 0 otherwise) [SI]2.958Traffic control (1 if yellow dashed line, 0 otherwise) [SI]3.154Violation (1 if careless operation, 0 otherwise) [SI]−2.8	68 143 42 20 14 469 95 21 28 9.576 602 802 21 68 58	3.78 -3.44 3.29 0.36 1.65 -4.92 4.02 0.08 2.20 -3.37 3.85 -4.07 2.29 1.77	0.000 0.000 0.001 0.708 0.073 0.000 0.000 0.625 0.018 0.001 0.000 0.000	-0.0076 - 0.0047 - -0.0143 - 0.0034 - 0.0166 - -0.0037	0.0066 - -0.0038 - 0.0128 - -0.0027 - -0.0127	0.0011 - -0.0008 - 0.0015 - -0.0007 - -0.0038
Bicycle movement (1 if normal movement, 0 otherwise) [SI] $-6.1$ Standard Deviation of Parameter, Normally Distributed 4.842 Traffic control (1 if stop sign, 0 otherwise) [SI] 0.720 Standard Deviation of Parameter, Normally Distributed 5.014 Alignment (1 if straight level, 0 otherwise) [SI] $-7.1$ Standard Deviation of Parameter, Normally Distributed 5.395 Posted speed limit (1 if between 50–60 mph, 0 otherwise) [SI] 0.121 Standard Deviation of Parameter, Normally Distributed 5.426 Highway type (1 if city street, 0 otherwise) [SI] -19. Standard Deviation of Parameter, Normally Distributed 16.66 Bicyclist race (1 if race 0, 0 otherwise) [SI] -6.81 Bicyclist age (1 if age $\geq$ 60 yrs.), 0 otherwise) [SI] 1.568 Prior movement (1 if entering or leaving, 0 otherwise) [SI] 2.955 Traffic control (1 if yellow dashed line, 0 otherwise) [SI] 3.154 Violation (1 if careless operation, 0 otherwise) [SI] -2.85	143 42 20 14 469 95 21 28 9.576 602 802 21 68 58	-3.44 3.29 0.36 1.65 -4.92 4.02 0.08 2.20 -3.37 3.85 -4.07 2.29 1.77	0.000 0.001 0.708 0.073 0.000 0.000 0.625 0.018 0.001 0.000 0.000	- 0.0047 - -0.0143 - 0.0034 - 0.0166 - -0.0037	- -0.0038 - 0.0128 - -0.0027 - -0.0127	-0.0008 -0.0015 0.0007 0.0038
Standard Deviation of Parameter, Normally Distributed4.842Traffic control (1 if stop sign, 0 otherwise) [SI]0.720Standard Deviation of Parameter, Normally Distributed5.014Alignment (1 if straight level, 0 otherwise) [SI] $-7.4$ Standard Deviation of Parameter, Normally Distributed5.395Posted speed limit (1 if between 50–60 mph, 0 otherwise) [SI]0.121Standard Deviation of Parameter, Normally Distributed5.426Highway type (1 if city street, 0 otherwise) [SI] $-19.$ Standard Deviation of Parameter, Normally Distributed16.60Bicyclist race (1 if race 0, 0 otherwise) [SI] $-6.8$ Bicyclist age (1 if age [50–59 yrs.], 0 otherwise) [SI]1.321Bicyclist age (1 if age [ $50-59$ yrs.], 0 otherwise) [SI]1.568Prior movement (1 if entering or leaving, 0 otherwise) [SI]2.958Traffic control (1 if yellow dashed line, 0 otherwise) [SI]3.154Violation (1 if careless operation, 0 otherwise) [SI] $-2.8$	42 20 14 469 95 21 28 9.576 602 802 21 68 58	3.29 0.36 1.65 -4.92 4.02 0.08 2.20 -3.37 3.85 -4.07 2.29 1.77	0.001 0.708 0.073 0.000 0.000 0.625 0.018 0.001 0.000 0.000	- 0.0047 - -0.0143 - 0.0034 - 0.0166 - -0.0037	- -0.0038 - 0.0128 - -0.0027 - -0.0127	-0.0008 -0.0015 0.0007 0.0038
Traffic control (1 if stop sign, 0 otherwise) [SI]  Standard Deviation of Parameter, Normally Distributed  Alignment (1 if straight level, 0 otherwise) [SI]  Standard Deviation of Parameter, Normally Distributed  5.3014  Standard Deviation of Parameter, Normally Distributed  5.428  Highway type (1 if city street, 0 otherwise) [SI]  Standard Deviation of Parameter, Normally Distributed  Highway type (1 if city street, 0 otherwise) [SI]  Standard Deviation of Parameter, Normally Distributed  Bicyclist race (1 if race 0, 0 otherwise) [SI]  Bicyclist age (1 if age [50–59 yrs.), 0 otherwise) [SI]  Prior movement (1 if entering or leaving, 0 otherwise) [SI]  Traffic control (1 if yellow dashed line, 0 otherwise) [SI]  Violation (1 if careless operation, 0 otherwise) [SI]  -2.8	20 14 469 95 21 28 9.576 602 802 21 68 58	0.36 1.65 -4.92 4.02 0.08 2.20 -3.37 3.85 -4.07 2.29 1.77	0.708 0.073 0.000 0.000 0.625 0.018 0.001 0.000 0.000	- -0.0143 - 0.0034 - 0.0166 - -0.0037	-0.0038 - 0.0128 - -0.0027 - -0.0127	- 0.0015 - -0.0007 - -0.0038
Standard Deviation of Parameter, Normally Distributed $5.014$ Alignment (1 if straight level, 0 otherwise) [SI] $-7.4$ Standard Deviation of Parameter, Normally Distributed $5.39$ Posted speed limit (1 if between $50-60$ mph, 0 otherwise) [SI] $0.12$ Standard Deviation of Parameter, Normally Distributed $5.428$ Highway type (1 if city street, 0 otherwise) [SI] $-19.$ Standard Deviation of Parameter, Normally Distributed $16.60$ Bicyclist race (1 if race $0.0$ otherwise) [SI] $-6.8$ Bicyclist age (1 if age $[50-59$ yrs.], 0 otherwise) [SI] $1.32$ Bicyclist age (1 if age $\ge 60$ yrs.), 0 otherwise) [SI] $1.52$ Prior movement (1 if entering or leaving, 0 otherwise) [SI] $2.95$ Traffic control (1 if yellow dashed line, 0 otherwise) [SI] $3.154$ Violation (1 if careless operation, 0 otherwise) [SI] $-2.8$	14 469 95 21 28 9.576 602 802 21 68 58	1.65 -4.92 4.02 0.08 2.20 -3.37 3.85 -4.07 2.29 1.77	0.073 0.000 0.000 0.625 0.018 0.001 0.000 0.000	- -0.0143 - 0.0034 - 0.0166 - -0.0037	- 0.0128 - -0.0027 - -0.0127	- 0.0015 - -0.0007 - -0.0038
Alignment (1 if straight level, 0 otherwise) [SI] -7.4  Standard Deviation of Parameter, Normally Distributed 5.395  Posted speed limit (1 if between 50-60 mph, 0 otherwise) [SI] 0.121  Standard Deviation of Parameter, Normally Distributed 5.428  Highway type (1 if city street, 0 otherwise) [SI] -19.  Standard Deviation of Parameter, Normally Distributed 16.60  Bicyclist race (1 if race 0, 0 otherwise) [SI] -6.88  Bicyclist age (1 if age [50-59 yrs.], 0 otherwise) [SI] 1.321  Bicyclist age (1 if age 2 of yrs.), 0 otherwise) [SI] 1.526  Prior movement (1 if entering or leaving, 0 otherwise) [SI] 2.958  Traffic control (1 if yellow dashed line, 0 otherwise) [SI] 3.154  Violation (1 if careless operation, 0 otherwise) [SI] -2.89	469 95 21 28 9.576 602 802 21 68 58	-4.92 4.02 0.08 2.20 -3.37 3.85 -4.07 2.29 1.77	0.000 0.000 0.625 0.018 0.001 0.000 0.000	0.0034 - 0.0166 - -0.0037	0.0128 - -0.0027 - -0.0127	0.0015 - -0.0007 - -0.0038
Standard Deviation of Parameter, Normally Distributed  5.395 Posted speed limit (1 if between 50–60 mph, 0 otherwise) [SI]  Standard Deviation of Parameter, Normally Distributed  5.428 Highway type (1 if city street, 0 otherwise) [SI]  Standard Deviation of Parameter, Normally Distributed  16.60 Bicyclist race (1 if race O, 0 otherwise) [SI]  Bicyclist age (1 if age [50–59 yrs.], 0 otherwise) [SI]  Bicyclist age (1 if age ≥ 60 yrs.), 0 otherwise) [SI]  Prior movement (1 if entering or leaving, 0 otherwise) [SI]  Traffic control (1 if yellow dashed line, 0 otherwise) [SI]  Violation (1 if careless operation, 0 otherwise) [SI]  -2.8	95 21 28 9.576 602 802 21 68 58	4.02 0.08 2.20 -3.37 3.85 -4.07 2.29 1.77	0.000 0.625 0.018 0.001 0.000 0.000 0.022	0.0034 - 0.0166 - -0.0037	-0.0027 -0.0127 -	-0.0007 - -0.0038
Posted speed limit (1 if between 50–60 mph, 0 otherwise) [SI] 0.121 Standard Deviation of Parameter, Normally Distributed 5.428 Highway type (1 if city street, 0 otherwise) [SI] -19. Standard Deviation of Parameter, Normally Distributed 16.66 Bicyclist race (1 if race O, 0 otherwise) [SI] -6.88 Bicyclist age (1 if age $[50–59 \text{ yrs.}]$ , 0 otherwise) [SI] 1.321 Bicyclist age (1 if age $[50-59 \text{ yrs.}]$ , 0 otherwise) [SI] 1.568 Prior movement (1 if entering or leaving, 0 otherwise) [SI] 2.958 Traffic control (1 if yellow dashed line, 0 otherwise) [SI] 3.154 Violation (1 if careless operation, 0 otherwise) [SI] -2.88	21 28 9.576 602 802 21 68 58	0.08 2.20 -3.37 3.85 -4.07 2.29 1.77	0.625 0.018 0.001 0.000 0.000 0.022	- 0.0166 - -0.0037	-0.0027 - -0.0127 -	-0.0007 - -0.0038 -
Standard Deviation of Parameter, Normally Distributed  5.428 Highway type (1 if city street, 0 otherwise) [SI]  5.428 Highway type (1 if city street, 0 otherwise) [SI]  5.428 Standard Deviation of Parameter, Normally Distributed  6.68 Bicyclist race (1 if race 0, 0 otherwise) [SI]  6.88 Bicyclist age (1 if age [50–59 yrs.], 0 otherwise) [SI]  7.28 Bicyclist age (1 if age > 60 yrs.), 0 otherwise) [SI]  7.56 Prior movement (1 if entering or leaving, 0 otherwise) [SI]  7.95 Traffic control (1 if yellow dashed line, 0 otherwise) [SI]  7.28 Violation (1 if careless operation, 0 otherwise) [SI]  7.28	28 9.576 602 802 21 68 58	2.20 -3.37 3.85 -4.07 2.29 1.77	0.018 0.001 0.000 0.000 0.022	- 0.0166 - -0.0037	- -0.0127 -	- -0.0038 -
Highway type (1 if city street, 0 otherwise) [SI] -19.  Standard Deviation of Parameter, Normally Distributed 16.60  Bicyclist race (1 if race 0, 0 otherwise) [SI] -6.81  Bicyclist age (1 if age [50–59 yrs.], 0 otherwise) [SI] 1.321  Bicyclist age (1 if age $\geq$ 60 yrs.), 0 otherwise) [SI] 1.568  Prior movement (1 if entering or leaving, 0 otherwise) [SI] 2.958  Traffic control (1 if yellow dashed line, 0 otherwise) [SI] 3.154  Violation (1 if careless operation, 0 otherwise) [SI] -2.89	9.576 602 802 21 68 58	-3.37 3.85 -4.07 2.29 1.77	0.001 0.000 0.000 0.022	- -0.0037	-0.0127 -	-
Standard Deviation of Parameter, Normally Distributed $16.60$ Bicyclist race (1 if race 0, 0 otherwise) [SI] $-6.8$ Bicyclist age (1 if age [50–59 yrs.], 0 otherwise) [SI] $1.32$ Bicyclist age (1 if age $\geq 60$ yrs.), 0 otherwise) [SI] $1.56$ Prior movement (1 if entering or leaving, 0 otherwise) [SI] $2.95$ Traffic control (1 if yellow dashed line, 0 otherwise) [SI] $3.154$ Violation (1 if careless operation, 0 otherwise) [SI] $-2.8$	602 802 21 68 58	3.85 -4.07 2.29 1.77	0.000 0.000 0.022	- -0.0037	-	-
$ \begin{array}{lll} \mbox{Bicyclist race (1 if race 0, 0 otherwise) [SI]} & -6.8 \\ \mbox{Bicyclist age (1 if age [50–59 yrs.], 0 otherwise) [SI]} & 1.32 \\ \mbox{Bicyclist age (1 if age $\geq 60 yrs.), 0 otherwise) [SI]} & 1.568 \\ \mbox{Prior movement (1 if entering or leaving, 0 otherwise) [SI]} & 2.958 \\ \mbox{Traffic control (1 if yellow dashed line, 0 otherwise) [SI]} & 3.154 \\ \mbox{Violation (1 if careless operation, 0 otherwise) [SI]} & -2.8 \\  \end{array} $	802 21 68 58 54	-4.07 2.29 1.77	0.000 0.022		0.0016	
$ \begin{array}{ll} \mbox{Bicyclist age (1 if age [50-59 \ yrs.], 0 \ otherwise) [SI]} & 1.321 \\ \mbox{Bicyclist age (1 if age $\geq 60 \ yrs.), 0 \ otherwise) [SI]} & 1.568 \\ \mbox{Prior movement (1 if entering or leaving, 0 \ otherwise) [SI]} & 2.958 \\ \mbox{Traffic control (1 if yellow dashed line, 0 \ otherwise) [SI]} & 3.154 \\ \mbox{Violation (1 if careless operation, 0 \ otherwise) [SI]} & -2.88 \\  \end{array} $	21 68 58 54	2.29 1.77	0.022			0.0020
Bicyclist age (1 if age $\geq$ 60 yrs.), 0 otherwise) [SI]1.568Prior movement (1 if entering or leaving, 0 otherwise) [SI]2.958Traffic control (1 if yellow dashed line, 0 otherwise) [SI]3.154Violation (1 if careless operation, 0 otherwise) [SI]-2.8	58 54	1.77	0.077	0.0030	-0.0026	-0.0004
Traffic control (1 if yellow dashed line, 0 otherwise) [SI] 3.154 Violation (1 if careless operation, 0 otherwise) [SI] -2.8	54	427	0.077	0.0016	-0.0014	-0.0002
Violation (1 if careless operation, 0 otherwise) [SI] -2.8		7.37	0.000	0.0038	-0.0031	-0.0006
	871	2.95	0.003	0.0041	-0.0035	-0.0006
Light condition (1 if dark with continuous streetlight, 0 otherwise) [SI] 1.794		-2.23	0.022	-0.0016	0.0013	0.0003
5	94	2.81	0.005	0.0039	-0.0032	-0.0007
Light condition (1 if dark streetlight at intersection only, 0 otherwise) [SI] 3.017		2.51	0.011	0.0020	-0.0016	-0.0003
Collision type (1 if head-on, 0 otherwise) [SI] 3.435		2.60	0.009	0.0019	-0.0016	-0.0003
Type of collision (1 if rear end, 0 otherwise) [SI] 5.812	12	4.65	0.000	0.0121	-0.0100	-0.0021
Minor Injury						
Constant [MI] -1.5		-6.70	0.000	-	-	-
Bicyclist race (1 if race W, 0 otherwise) [MI] 3.964		15.05	0.000	-0.0175	0.1228	-0.1053
Highway type (1 if state highway, 0 otherwise) [MI] 0.449		2.37	0.018	-0.0014	0.0059	-0.0045
Type of collision (1 if making left turn, 0 otherwise) [MI] 0.438 Weather condition (1 if rain, 0 otherwise) [MI] 0.877		1.65	0.098 0.018	-0.0002 $-0.0003$	0.0021 0.0022	-0.0019 $-0.0018$
Bicyclist age (1 if age (20–34 yrs.), 0 otherwise) [MI]		2.35 6.45	0.000	-0.0003 -0.0008	0.0022	-0.0018 -0.0101
Standard Deviation of Parameter, Normally Distributed  3.620		5.66	0.000	-0.0008	-	-0.0101
No injury	20	5.00	0.000			
Driver gender (1 if male, 0 otherwise) [NI] —2.1	181 -	-10.58	0.000	-0.0033	-0.0398	0.0431
Standard Deviation of Parameter, Normally Distributed 4.047		10.89	0.000	-	-	-
Bicyclist age (1 if age 19 yrs. or less, 0 otherwise) [NI] -0.73		-2.64	0.008	0.0000	0.0015	-0.0015
Standard Deviation of Parameter, Normally Distributed 1.166		1.87	0.056	-	_	-
Traffic control (1 if no control, 0 otherwise) [NI] 0.281		1.92	0.055	-0.0001	-0.0055	0.0056
Posted speed (1 if posted speed 30 mph or less, 0 otherwise) [NI] 0.354	54	2.50	0.012	-0.0003	-0.0126	0.0129
Bicyclist race (1 if race B, 0 otherwise) [NI] -3.6	627 -	-12.37	0.000	0.0024	0.0799	-0.0823
Harm event, (1 if motor vehicle in transport, 0 otherwise) [NI] $-0.4$	483	-3.26	0.001	0.0007	0.0236	-0.0243
Location type (1 if Business, Industrial, Manufacturing, 0 otherwise) [NI] 0.381	81	2.54	0.011	-0.0005	-0.0167	0.0171
Heterogeneity in the means of the random parameters						
Straight level alignment [SI]: Bicyclist race (1 if race W, 0 otherwise)  3.461	61	4.20	0.000	-	_	-
Bicyclist age (20–34) yrs.) [MI]: Bicyclist race (1 if race W, 0 otherwise) –0.9.		-2.37	0.005	-	_	-
Male driver [NI]: Bicyclist race (1 if race W, 0 otherwise) 0.703		2.24	0.012	-	-	-
Bicyclist age (19 yrs. or less) [NI]: Bicyclist race (1 if race W, 0 otherwise) 0.665	65	1.76	0.078	-	-	-
Heterogeneity in the variances of the random parameters						
Normal movement [SI]: Bicyclist race (1 if race O, 0 otherwise) 0.66	6	1.95	0.046	-	-	-
Straight level alignment [SI]: Bicyclist race (1 if race O, 0 otherwise) 0.390  Model statistics	90	2.02	0.043	-	-	-
	935.98					
	520.77					
McFadden Pseudo R-squared 0.416						
AIC 7986						
No. of observation 6136						

The modeling results also revealed that crashes on roadways with posted speed limits between 50–60 mph are likely to have an increased propensity for severe injuries (ME = 0.0034), which is likely as driving at high speeds leaves drivers little time to react and avoid a crash. Moreover, exposure to high speeds increases the vulnerability of bicyclists. Consistent with findings from other studies, high-speed limits increase the chance for severe/fatal injuries (Chen and Shen, 2016; Rash-ha Wahi et al., 2018). Defined for the severe injury category, the variable for speed limit between 50–60 mph was found to pro-

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duce statistically significant random parameters with a normal distribution (mean = 0.122, and standard deviation = 5.428). This distribution implies that 49.11 % of crashes on roads with a speed limit between 50–60 mph will have a decreased likelihood of severe injuries in crashes.

Looking at highway type (1 if city street, 0 otherwise), the indicator variable predicted an increase in the probability of severe injury for 11.92 % percent of the crashes while decreasing the probability of severe injury for the other 88.08 %. This finding indicates that for crashes that occur on the city street, most of them are less likely to result in severe injuries. City streets have complex driving and cycling environments and lower speed limits. Both drivers and bicyclists are riding with relatively higher caution. Therefore, severe injuries are less likely to happen on such roads (Rifaat et al., 2011).

To understand how the characteristics pertaining to the bicyclist influenced the injury severity outcomes, the study explored indicator variables, namely the bicyclists' race and age. The indicator for bicyclists of race other that Black Americans and Caucasians (1 if race others or O, 0 otherwise) was found to be a significant variable that decreased the likelihood of severe injuries by -0.0037 and increased the likelihood of minor and no injuries by 0.0016 and 0.0020, respectively. On the contrary, bicyclists aged between 50–59 years and those over 60 years were likely to have increased injury severity outcomes. From the marginal effect estimates, these indicator variables increased the probability of severe injury and decreased the probability of minor and no injuries. These findings are in line with studies in the literature (Liu et al., 2020; Yan et al., 2011), and are plausible as seniors have increased perception and reaction times, making them more susceptible to roadway fatalities.

Careless operation, defined for the severe injury category, was found to be a statistically significant fixed parameter. From the marginal effect estimate, it was identified that careless operation reduced the possibility of observing a severe injury outcome by -0.0016 and increased the possibility of observing both minor and no injury outcomes by 0.0013 and 0.0003, respectively. This finding seems counterintuitive as violations, in general, are likely to increase the probability of severe injury (Behnood and Mannering, 2017a, 2017b). This variation in result may be due to the differences in the datasets in terms of roadway type and speed on the roads on which the crashes occurred.

Poorly lit environments in dark light conditions were likely to increase the chance of obtaining severe injury outcomes in vehicle-bicycle crashes. Defined for severe injury category, both variables for the light condition in the dark with continuous streetlight and light condition in dark streetlight at the intersection were found to be significant variables, and they were found to increase the likelihood of severe injuries and decrease the likelihood of minor and no injuries, as shown in Table 3. These findings are in tandem with previous studies. Darkness, with or without streetlights, was identified to increase the probability of bicyclists having fatal/severe injury by a large margin (Kim et al., 2007; Liu et al., 2020), which can be attributed to the low visibility of bicyclists. Besides, as most tired/drowsy drivers continue to speed and fail to adjust their speeds to the dark conditions during the night or in dark conditions (Tamakloe et al., 2021), there is a high chance that the impact of a crash of a less visible bicyclist would be high, resulting in fatalities.

Finally, the indicator variables for head-on and rear-end collisions defined for the severe injury category also produced statistically significant fixed parameters. Intuitively, from the marginal effect estimates, both indicator variables increased severe injury outcomes and a decrease in minor no injury outcomes. Kim et al. (2007) indicate that head-on vehicle-bicycle crashes are likely to be fatal. In general, these types of crashes are caused by cycling while facing traffic. Besides, the study by Yan et al. (2011) identified that injuries sustained in rear-end vehicle-bicycle crashes mostly occur at the blind-sight of bicyclists and are likely to be severe. These findings are likely, as the bicyclist is unaware of the oncoming vehicle and is not able to respond appropriately to avert the crash.

#### 5.2. Minor injury

Interesting findings regarding the bicyclists' race were identified. Defined for the minor injury category, the indicator variable for Caucasian/white bicyclists (1 if race W, 0 otherwise) was found to raise the likelihood of minor injury by 0.1228 and decrease the likelihood of severe and no injury outcomes by -0.0175 and -0.1053, respectively. Similar to the case of Louisiana, White bicyclists from Los Angeles were also identified to have a high propensity for minor injuries and reduced probabilities for severe and no injuries relative to other races (Behnood and Mannering, 2017a, 2017b).

The state highway indicator resulted in more minor crashes as it is shown by positive marginal effects for minor injury (0.0059) and negative marginal effects for severe (-0.0014) and no injuries (-0.0045) outcomes. In existing studies, researchers found that increasing speed limits could result in more severe crashes for bicyclists (Rifaat et al., 2011). However, the results from our study suggest that state highways are associated with minor injuries. The reason could be that the highway typically has fewer bicyclists and no bike lanes, thus having fewer vehicle-bicycle crashes. If the highway has to be shared with bicyclists in some unique scenario, both drivers and bicyclists will pay extra attention to that complex environment.

The indicator variables for drivers making left turns and rainy weather were identified to correlate positively with minor injury outcomes. From the marginal effect estimates, the probability that left turn and rainy-weather-related vehicle-bicycle collisions would yield minor injuries increases by 0.0021 and 0.0022, respectively. It is noteworthy that the probability for both severe and no injury outcomes are likely to decrease in both cases. In the literature, inclement weather was identified to be a significant predictor of bicyclist injury severity. As established by Yan et al. (2011), bicyclists are likely to ride carefully

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due to the reduced visibility; thus, reducing the chance for fatal injury severities in the event of a crash. Besides, it has also been shown that the probability of being severely injured is reduced during rainy weather (Sivasankaran and Balasubramanian, 2020). The finding regarding driver-bicyclist left turn negotiation crashes is consistent with the literature. According to Nicholls et al. (2017), left turn crashes involving bicyclists are proportionally less severe. Again, as intersections and left-turning maneuvers are complex in nature, there is a high probability that road users would be more careful. As such, instead of having fatal crashes, bicyclists may have minor injuries in the event of a left turn-related crash. Abdel-Aty and Keller (2005) identified that left turn-related crashes are likely to occur with increased traffic volume and left turning lanes. It is appropriate to factor these variables when developing intersection safety improvement strategies to check vehicle-bicycle left turn-related collisions.

Furthermore, the indicator for the age of bicyclists between 20-34 increased the probability for minor injuries by 0.0109 and decreased that of severe and no injury outcomes by -0.0008 and -0.0101, respectively. This variable was identified as a random parameter and normally distributed with a mean of 1.48824 and a standard deviation of 3.62004 in the minor injury model. According to this, about 34.05% of the drivers between 20-34 are related to minor injury prospects. In other words, 34.05% of the distribution is less than 0, and the remaining 65.95% is more than 0. As previously identified, and in line with previous research, this age group is less likely to be involved in fatal crashes due to their low reaction and perception times as compared to older riders who are more fragile and susceptible to fatal injury severity outcomes (Behnood and Mannering, 2017a, 2017b).

#### 5.3. No injury

Regarding the bicyclist's sex, the study identified that male bicyclists were more likely to have no injuries. From the marginal effects estimates, while the probability for no injuries increased by 0.0431, that of severe injury and minor injuries reduced by -0.0033 and -0.0398, respectively. This indicator variable was found to be a normally distributed random parameter with a mean of -2.18147 and a standard deviation of 4.04796. These distributional values imply that male driver increases the no injury outcome by 29.5 %. The findings regarding this variable in the literature have been contradictory. While some studies identified that males are more susceptible to fatal crashes due to their risk-taking behaviors and their higher tendencies of breaking traffic rules, (Behnood and Mannering, 2017a, 2017b; Rash-ha Wahi et al., 2018), others showed that they are less likely to be involved in fatal collisions compared to females due to the perception that males are more experienced at riding (Liu et al., 2020). There is the need to perform a more comprehensive study to identify how collisions between both bicyclist groups differ in terms of severity outcomes.

Also, the distribution of bicyclists, who are 19 years or less, shows that this variable increases the likelihood of no injury for 27 % of the observations. Traffic with no control crashes resulted in an increased possibility of no injury (ME = 0.0056) and a reduction in the probability of severe (ME = -0.0001) and minor injury outcomes (ME = -0.0055). In particular, the probability for no injury outcomes increase by 0.0056 when the crash occurs at a segment with no control present. This finding is likely, as both bicyclists and drivers compensate for the lack of traffic control at these segments by driving/riding carefully. Behnood and Mannering (2017a, 2017b) also had a similar result in their study. According to their research, vehicle-bicycle crashes at segments with non-functional traffic signals (no control present) are likely to have an increase in the probability of no injury outcomes.

Concerning the indicator variable for posted speed, the study identified that vehicle-bicycle collisions on roads with posted speeds of 30 mph are likely to have an increase in the likelihood of no injuries. This association is supported by negative marginal effects for minor and severe injuries and positive marginal effects for no injury's outcome. This finding aligns with the literature (Islam and Hossain, 2015) and is intuitive as these roads have lower speeds. Thus, drivers are able to react in time in vehicle-bicycle conflict situations. As identified by (Yan et al., 2011), higher speeds tend to reduce the time taken by drivers to react to emergencies. The authors added that bicyclists on such roads are also likely not to give way as they make turning maneuvers at give way-controlled intersections, leading to fatalities in the event of a bicycle-involved crash.

The results in Table 3 show that bicyclists identified to be African Americans (1 if race African American, 0 otherwise) are more likely to have an increased possibility of severe (ME = 0.0024) and minor injury (ME = 0.0799) outcomes. Besides, this indicator variable was found to decrease the possibility of no injury by -0.0823. It is noteworthy that this finding was not in line with that reported by Behnood and Mannering (2017a, 2017b) and may be due to the difference in the riding behavior in both jurisdictions. The harmful event variable (1 if a motor vehicle in transport, 0 otherwise), resulted in less no injuries outcome (negative marginal effects for no injury and positive marginal effects for severe and minor injuries outcome). Lastly, location type (1 if a business, industrial, manufacturing, 0 otherwise) [NI] increased the likelihood of no injuries by 0.0171 and decreased the likelihood of severe and minor injuries by -0.0005 and -0.0167, respectively. Although vehicle-bicycle crashes are likely to be common in commercial areas due to increased vehicle-bicycle conflicts (Ding et al., 2020; Hong et al., 2020), the crashes are likely to result in no injuries. In a previous study conducted by Islam and Hossain (2015), it was found that bicyclists are less likely to be involved in fatal and minor injury crashes in commercial areas in Alabama. Essentially, as these locations are busy environments, they are designed to accommodate bicyclists and vehicles appropriately. Besides, the speeds in these places may be lower due to high traffic volumes, making it safer for bicyclists.

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## 5.4. Heterogeneity in mean and variance measures of the random parameters

All explanatory variables in the mixed logit model were tested for possible heterogeneity in the random parameters' mean and variance measures. The final model showed four substantial heterogeneities in means of the same random parameter as shown in Table 3, whereas two of them showed some heterogeneity variances of another random parameter.

Straight level alignment was found to expressively increase the mean of the random parameter for Caucasian bicyclists. This suggests more severe injury severity when those drivers drive in straight alignment. The bicyclist race also found an effect by specific bicyclist age. The results show decreases in the minor crash injuries of the random parameters when bicyclist age is between 20 to 34 years old. Also, crashes for bicyclists aged 19 years old or younger increase the mean of no injury for the Caucasian bicyclist parameter and the male bicyclist. This means more no injury injuries for male Caucasian bicyclists.

The result of the mixed logit model of the vehicle-bicycle crashes (Table 3) listed two variables affecting the variance of the same of the random parameters. Normal bicycle movement at the crash scene and straight level alignment increase the variance of bicyclists with other racial backgrounds.

## 5.5. Key findings

The analysis conducted in this study resulted in identifying key insights leading to the proposal of countermeasures to increase bicyclist safety. First, the finding that the probability of severe injury rises by 11.8 percent if a distracted driver is involved in the crash highlights that distracted driving is potentially very dangerous and increases the vulnerability of non-motorists. Besides, careless operations could lead to a higher frequency of crashes with severe injuries. In general, these findings are intuitive as a violation of traffic rules and careless driving/operation is likely to lead to severe crashes. In the literature, distraction-related driving was found to be associated with severe ramifications, particularly in curved sections and around work zones (Lym and Chen, 2021). According to Chandia-Poblete et al. (2021), aside from being one of the leading causes of crashes in Chile, destructed driving has been identified as a significant cause of severe injury crashes between motorists and bicyclists as it is mainly associated with speeding. To reduce the severity of these crashes, it is imperative to consider speed reduction measures, particularly on roads where bicyclists frequently use them. Besides, securing the safety of bicyclists by improving the existing bicycle lanes and providing more bicyclist accommodation facilities would be helpful as it reduces vehicle-bicycle conflicts. While educational campaigns would also be helpful to sensitize drivers on the dangers of careless operation of vehicles and engaging in secondary activities while driving, using both mobile and fixed artificial intelligence-enabled cameras to capture, detect, and punish drivers caught in these acts, would help maximize safety.

The study identified that straight-level roadways decrease the probability of severe injury but increase the chance of minor injuries in crashes involving bicyclists. Besides, the finding that bicyclists of the Caucasian race are likely to have an increase in injury severity on straight level roads may be due to some riders/drivers being less careful due to the perceived level of safety associated with such roads. Intuitively, the longer the straight section there is, the higher the tendency of being less careful and speeding. According to the literature, some road users are likely to engage in risky behaviors, relax, or become drowsy or distracted when driving on roads with straight and leveled alignments (Tamakloe et al., 2020), which may increase the chance of run-off-road crashes and endangering the lives of road-users at the periphery of the road. It would be worthwhile to encourage both riders and drivers to stay alert as they use the roadway irrespective of the alignment type. Besides, considering the re-engineering of road edge strips (for example, constructing rumble strips or installing LED studs on the edge lines), such that it guides drivers could help reduce these kinds of crashes.

In general, although city streets were identified to be less likely to be associated with severe injuries, the analysis results identified that a sizeable proportion of vehicle-bicycle crashes (11.92 % percent) are likely to have an increase in the probability of severe injury on them. City street roads are designed to have lower speeds. Nevertheless, the increase in bicycle infrastructure led to a corresponding increase in bicycle users (Parker et al., 2011), thus increasing the chance for many crashes between them. Besides, this group's increased fatality of crashes may be due to delayed response due to the high likelihood of hit-and-run vehicle-bicycle cases on the Louisianian roads (Das et al., 2019). Further, there are still many miles of unprotected bike lanes in Louisiana (Bike Easy, 2021). To improve the safety of bicyclists, there is the need to focus on improving those bicycle lanes in poor condition, adding more miles of protected bicycle lanes, and implementing enforcement-related policies targeted at severely punishing drivers caught in a hit and run case. It would be worthwhile allocating funds for the development of emergency care facilities that encourage quick response to vehicle-bicycle crashes.

The finding that old-aged riders are likely to be seriously injured in vehicle-bicycle crashes in Louisiana is consistent with previous literature. Nevertheless, there are generally limited safety programs that seek to improve the safety of senior bicyclists. To reduce these kinds of crashes, there is a need to increase funding for projects geared at designing and constructing complete networks that support all road user types, particularly senior bicyclists. Increasing the visibility of road signs could help keep seniors informed, and educating them on the need to wear protective gear and ride carefully on the roadways could help reduce vehicle-bicycle crash mortality.

Finally, while encouraging bicyclists to prepare adequately by wearing reflective clothing while riding at night could reduce the injury severities associated with night riding, it would be worthwhile to ensure that bicycles are fitted with appropriate lighting to increase the visibility of the riders during the night. Enforcement would be needed to ensure that riders follow the required measures prescribed for riding at night. Besides, with the recent developments in lighting

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technology, there is the need to re-evaluate and adjust the road lighting standards/recommended levels of luminance to ensure that roadways are well lit during the night.

The significant findings of this study are summarized as follows:

- The probability of severe injury rises by 11.8 percent if a distracted driver is involved.
- Straight level roadway decreases the probability of severe injury in the crashes involving bicyclists
- City streets are less likely to associate with severe injuries
- Elderly bicyclists are more likely to have severe injuries if a crash occurred
- Careless operations could lead to a higher frequency of crashes with severe injuries
- Light condition in the dark with streetlight is associated with severe injuries

## 6. Conclusions

Although cycling has become a popular transport mode, the safety issue is one of the major barriers to the wide adoption of cycling as a short-distance and/or short-duration transportation mode. The current study provides new insights into the influential factors (from a wide range of factors) affecting bicyclist injuries in Louisiana by using a mixed logit model with heterogeneity in the means and variances. The approach accounts for the influence of unobserved heterogeneity, recognizing that the sources of unobserved heterogeneity are not independent. The correlation among these parameters provides additional insights on unobserved factors, whereas the heterogeneity-in-the-means structure depicts the effect of undetected factors on the distributional properties of the random parameters. Essentially, accounting for various levels of unobserved heterogeneity provided a deeper understanding of the factors influencing bicyclist injury severity in Louisiana. The study found that distracted drivers, elder bicyclists, careless operations, and light conditions in the dark with streetlights are highly associated with severe injuries. Moreover, straight-level roadway and city streets decrease the odds of severe injuries.

Based on the study findings, several general recommendations have been provided. There is a need for additional focus in providing lighting at night in high bicyclist exposure areas and crash hotspots. Additionally, attention is needed in setting posted speed limits based on facility type, bicyclist exposure, and crashes. Targeted safety education campaigns and safety campaigning via focus groups or social media can be beneficial in educating bicyclists on safety measures so that violations from their end can be prohibited.

The current study has limitations. First, this study used police-reported crash data. No injury or minor injury bicycle crashes are often not reported. Exclusion of many of the crashes due to their absence in the police-reported crash can generate selection bias. This bias can be reduced by using methods simultaneous equation modeling, which is out of the scope of this study. Second, this study did not use bicyclist crash typing data due to its unavailability. Crash typing data provides more information on the crash occurrences, such as bicyclists' locations and bicyclist action. Addressing the selection bias issue and including more realistic variables such as crash typing variables can be considered two research areas for future researchers.

## **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.

## Acknowledgments

The authors like to thank three anonymous reviewers for their excellent suggestions.

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# Appendix A

(See Table A1).

Table A1 Proportions of key attributes by severity types.

Attributes	Severe (N = 390)	Minor (N = 4449)	No Injury (N = 1297)	p-valu
Driver Condition				<0.001
Distracted	99 (25.4 %)	1594 (35.8 %)	374 (28.8 %)	
Others	291 (74.6 %)	2855 (64.2 %)	923 (71.2 %)	
Bicyclist Race	, , ,	,	,	< 0.001
B (African American)	173 (44.4 %)	2071 (46.5 %)	384 (29.6 %)	
O (Other Ethnicity)	20 (5.13 %)	232 (5.21 %)	403 (31.1 %)	
W (Caucasian)	197 (50.5 %)	2146 (48.2 %)	510 (39.3 %)	
Bicyclist Gender	137 (30.3 %)	21 10 (10.2 %)	310 (33.3 %)	< 0.001
Male	339 (86.9 %)	3604 (81.0 %)	818 (63.1 %)	١٥.٥٥١
Others	, ,	, ,	, ,	
Bicyclist Age	51 (13.1 %)	845 (19.0 %)	479 (36.9 %)	40 001
, ,	00 (22 1 %)	1120 (25.2.%)	222 (17.2.9/)	<0.001
19 yrs. or less	90 (23.1 %)	1120 (25.2 %)	223 (17.2 %)	
20–34 yrs.	75 (19.2 %)	1252 (28.1 %)	346 (26.7 %)	
35–49 yrs.	85 (21.8 %)	893 (20.1 %)	165 (12.7 %)	
50–59 yrs.	95 (24.4 %)	742 (16.7 %)	145 (11.2 %)	
60 yrs. or older	39 (10.0 %)	373 (8.38 %)	52 (4.01 %)	
Unknown	6 (1.54 %)	69 (1.55 %)	366 (28.2 %)	
Driver Violation				< 0.001
Careless operation	19 (4.87 %)	286 (6.43 %)	122 (9.41 %)	
Others	371 (95.1 %)	4163 (93.6 %)	1175 (90.6 %)	
Harmful Event	` ,	` ,	` ,	< 0.001
Motor Vehicle in Transport	316 (81.0 %)	3588 (80.6 %)	940 (72.5 %)	
Others	74 (19.0 %)	861 (19.4 %)	357 (27.5 %)	
Bicycle movement	74 (15.0 %)	001 (15.4 %)	337 (27.3 %)	<0.001
	126 (22.2 %)	1952 (41.6.%)	456 (35.2 %)	<b>\0.001</b>
Normal Movement	126 (32.3 %)	1853 (41.6 %)	` ,	
Others	264 (67.7 %)	2596 (58.4 %)	841 (64.8 %)	0.000
Prior Movement	40 (40 0 0)	2.45 (5.00.00)	0.4 (5.05.00)	0.002
Entering or leaving	49 (12.6 %)	347 (7.80 %)	94 (7.25 %)	
Others	341 (87.4 %)	4102 (92.2 %)	1203 (92.8 %)	
Collision Type				<0.001
Head-On	23 (5.90 %)	120 (2.70 %)	32 (2.47 %)	
Left Turn	24 (6.15 %)	334 (7.51 %)	71 (5.47 %)	
Rear End	93 (23.8 %)	348 (7.82 %)	102 (7.86 %)	
Others	250 (64.1 %)	3647 (82.0 %)	1092 (84.2 %)	
Highway Type				< 0.001
City Street	162 (41.5 %)	2482 (55.8 %)	819 (63.1 %)	
State Hwy	112 (28.7 %)	878 (19.7 %)	177 (13.6 %)	
Others	116 (29.7 %)	1089 (24.5 %)	301 (23.2 %)	
Location	110 (25.7 %)	1003 (24.3 %)	301 (23.2 %)	0.001
	222 (50 5 %)	3903 (GE 0 %)	909 (60.2 %)	0.001
Business, Industrial, Manufacturing	232 (59.5 %)	2892 (65.0 %)	898 (69.2 %)	
Others	158 (40.5 %)	1557 (35.0 %)	399 (30.8 %)	0.004
Traffic Control				<0.001
No Control	75 (19.2 %)	1243 (27.9 %)	407 (31.4 %)	
Stop Sign	58 (14.9 %)	645 (14.5 %)	177 (13.6 %)	
Yellow Dashed Line	53 (13.6 %)	243 (5.46 %)	40 (3.08 %)	
Others	204 (52.3 %)	2318 (52.1 %)	673 (51.9 %)	
Posted Speed Limit				< 0.001
30 mph or less	152 (39.0 %)	2262 (50.8 %)	734 (56.6 %)	
Others	238 (61.0 %)	2187 (49.2 %)	563 (43.4 %)	
Alignment	` ,	` ,	` ,	< 0.001
Straight-Level	347 (89.0 %)	4216 (94.8 %)	1248 (96.2 %)	
Others	43 (11.0 %)	233 (5.24 %)	49 (3.78 %)	
Others Lighting Condition	(11.0 %)	233 (3.24 %)	T3 (3.70 %)	<0.001
Dark - Continuous Street Light	80 (20.5 %)	721 (16.2 %)	229 (17.7 %)	\0.001
		, ,	` ,	
Dark - No Street Lights	61 (15.6 %)	189 (4.25 %)	43 (3.32 %)	
Others	249 (63.8 %)	3539 (79.5 %)	1025 (79.0 %)	
Weather				0.054
Rain	18 (4.62 %)	186 (4.18 %)	36 (2.78 %)	
Others	372 (95.4 %)	4263 (95.8 %)	1261 (97.2 %)	

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## **Further Reading**

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