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RESEARCH ARTICLE

The Effect of Age on Motorcyclist Injury Severities in Multi-Vehicle Motorcycle Crashes: Accounting for Unobserved Heterogeneity and Insights From Out-of-Sample Prediction

YU HUANG[1], YANYING WANG[1], LE TIAN[1], AND CHUNHUI ZHANG[2]
[1]China Communications Information Technology Group Company Ltd., Beijing 100088, China
[2]North China Municipal Engineering Design and Research Institute Company Ltd., Tianjin 300110, China

Corresponding author: Le Tian (tl18120752@163.com)

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ABSTRACT This paper studies the factors affecting injury severities involving motorcyclists of different age groups (under 25, 25-55, 55 and above) based on the random parameter logit model. Data collected from motorcycle crashes in the UK between 2017 and 2020 are utilized. The motorcyclist injury severity outcomes are categorized as follows: minor injury, severe injury, and fatal injury. The results of the likelihood ratio tests showed that transferability in multi-vehicle motorcycle crash injury severity involving motorcyclists of different age groups. The results of the modeling revealed significant variations in the factors that impact motorcycle crashes among three different age groups, including rider characteristics (such as male riders), motorcycle and non-motorcycle characteristics (such as vehicle running status preceding collision, age of the vehicle, and non-motorcycle vehicle type), roadway and environmental conditions (such as weather condition, speed limit, and road type), temporal-related characteristics (such as day of the week), and crash-related characteristics (such as crash types). The models demonstrate the existence of unobserved heterogeneity for three statistically significant variables, including the truck-involved, rear-end collision, and morning off-peak hours indicator in the under 25 age group crash model, and vehicle straight movement in the 25-55 age group crash model, and passenger car and sideswipe in the 55 and above age group crash model. Further, there are substantial differences in injury severity probabilities involving motorcyclists of different age groups by comparing prediction results based on out-of-sample prediction simulation. This paper emphasized the importance of revealing different age groups' crash transferability and heterogeneity. The statistically significant differences involving age group crash injury severity models highlight the importance of age-targeted policies for motorcycle safety.

INDEX TERMS Multi-vehicle motorcycle crashes, age groups, injury severity, random parameters logit model, out-of-sample prediction.

I. INTRODUCTION

Traffic safety is a profound public safety challenge being faced within the world. Each year, approximately 1.3 million people lose their lives due to road traffic accidents, with motorcyclists accounting for about 28% of all road traffic deaths globally [1]. Compared to other motorized road users, motorcyclists typically face higher risks of injury and death due to the lack of protective features in the event of a collision. In the UK, motorcycle riders have around fifty times (121 vs. 2.26) the death rate in road traffic accidents, compared to car drivers, per mile traveled, based on averaging data over recent years (years 2012 to 2016) [2]. In the United States, the fatality rate of motorcyclists per vehicle-mile-traveled (VMT)

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is approximately 27 times higher than that of passenger car occupants [3]. This significant disparity underscores the importance of gaining a deeper understanding of the various interconnected factors that contribute to the severity of injuries sustained by motorcyclists in crashes by identifying and implementing effective countermeasures, lives can be saved.

Among the many factors, abundant recent research efforts stated that the injury severities of motorcyclists increased with age [4], [5], [6], [7], [8], [9], [10]. However, in the majority of motorcycle crash studies, it was considered that the age of the motorcyclist could serve as an indicator variable. As a result, these studies could not identify some important factors unique to motorcyclists of different age groups. It is probable that the impact of influencing factors on the severity of injuries sustained by motorcyclists would vary, involving motorcyclists of different age groups. The largest fatalities fall within older motorcyclists when contrasted with younger age cohorts. Older motorcyclists have the lowest number of casualties when considering all casualties [11]. There are many causes for these problems. As an example, driving experience tends to increase with age, but physical degradation can also set in, leading to longer reaction times, diminished cognitive processing abilities, and reduced vision and hearing capacity [12]. Due to this difference, injury severity has been analyzed for motorcyclists of different age groups separately. Based on the divergence involving motorcyclists of different age groups, several targeted elaborate recommendations can be implemented to alleviate the injuries and fatalities of motorcyclists.

Unobserved heterogeneity is also a major challenge in current traffic safety research literature. To effectively account for unobserved heterogeneity, various heterogeneity modeling approaches are utilized to examine the factors that contribute to the severity of injuries sustained by motorcyclists, including the random parameters (also called mixed) models [13], [14], and latent class models [15], [16], [17]. According to the research, accounting for unobserved heterogeneity by taking into account factors that vary among observations can improve the modeling of the intricate interplay between different variables, as well as the characteristics of the injuries [13].

Besides the typical pair test employed to compute the log-likelihood of data for estimated parameters of motorcyclists from an alternate age group [18], another suitable approach is the use of out-of-sample prediction, which is increasingly employed in literature to investigate the non-transferability of estimated parameters [19], [20], [21], [22], [23], [24], [25]. To assess the likelihood of non-transferability among different decomposition subgroup datasets, out-of-sample predictions were carried out to determine the probability differences based on the estimated parameters.

This paper aims to examine the factors affecting injury severity among motorcyclists in various age groups, using UK motorcycle crash data from 2017 to 2020. To account for unobserved heterogeneity, a random parameter logit model was employed in this study. The study is unique in two ways: (1) it investigates the differences and unobserved heterogeneity among different age groups of motorcyclists; and (2) it conducts an extensive set of out-of-sample prediction simulations to gain a better understanding of the variations in injury severity distribution among motorcyclists across various age groups.

The paper is structured as follows: Section II presents a review of relevant literature on the impact of age and methodologies on motorcyclist outcomes. Section III outlines the data utilized in this study, while Section IV details the methodology employed. Likelihood ratio tests are used to examine non-transferability, and the estimated results are subsequently presented and discussed in Section V. The paper concludes with a summary of findings, implications, and potential areas for future research.

II. LITERATURE REVIEW

Table 1 summarizes previous studies' findings on the impact of motorcyclists' age and methodologies. These investigations have examined diverse factors, including rider and vehicle characteristics, environmental and roadway conditions, helmet use, alcohol impairment, and other associated factors on injury severity in motorcycle accidents. Regarding age attributes, abundant recent research stated that the injury severities of motorcyclists increased with age [4], [5], [6], [7], [8], [9], [10]. For example, Alnawmasi and Mannering [26] found that motorcyclists over 60 tend to suffer from severe injuries. Wang et al. [27] and Chang et al. [28] stated that motorcyclists over 50 and 59 years old have a higher likelihood of being involved in fatal motorcycle crashes. However, in most motorcycle crash studies, the motorcyclist's age was considered an indicator variable (See Table 1). As a result, these studies could not identify some important factors unique to motorcyclists of different age groups. Note that Islam [29] analyzed the effects of three age groups (under 30, 30–49, and 50 and above) on motorcyclists. However, their study was constrained to single-vehicle crashes. Prior studies did not present separate performance models for multi-vehicle motorcycle crashes – to the best of the author's knowledge. It should be noted that the severity of multi-vehicle motorcycle crashes is more complex than single-vehicle motorcycle crashes, thus necessitating an in-depth analysis.

Traditional logit and probit models have been commonly utilized to examine the factors that influence motorcyclist injury severities [4], [6], [7], [8], [9], [10], [30], [31], [32], [33]. However, these models assume that estimated parameters are constant across all observations, which may result in biased estimates and incorrect inferences [34]. Moreover, traditional crash databases often lack pertinent information that may impact crash injury severity, leading to unobserved heterogeneity. To address this, random parameters models (also known as mixed models) and their extensions have been widely employed to investigate factors affecting motorcyclist injury severity [13], [14]. However, the use of this method in analyzing injury severities among

TABLE 1. A review of findings about the effects of motorcyclists' age on injury severity.

Author	Methodology	Findings
Chang et al. [16]	The latent class random parameter ordered logit models	The rider's age reflected the temporal heterogeneity across different years. Overall, there is a higher likelihood of severe injury among riders aged 25-44, 45-64, and over 64, compared to those under 24.
Chang et al. [28]	Random parameters binary-ordered probit model	Riders over 59 are crucial factors influencing riders' injury levels.
Islam and Brown [14]	Random parameter logit models	Older motorcyclists (over 65) are more likely to suffer serious injuries.
Schneider IV and Savolainen [10]; Shankar and Fred Mannering [4];	Multinomial logit model	The likelihood of fatality and incapacitating injury in motorcycle crashes increases with age.
Lapparent [5]	Empirical Bayesian method	Individuals in the age range of 30-50 years who identify as women and ride high-performance motorcycles are at the greatest risk of sustaining injuries while on the road.
Savolainen and Mannering [7]	Nested logit models	Motorcyclists who are advanced in age have a higher likelihood of experiencing severe injuries.
Alnawmasi and Mannering [26]	Random parameters logit models with heterogeneity in means and variances	Individuals who are 60 years or older and ride motorcycles have a greater probability of sustaining severe injuries.
Pai and Saleh [6, 8, 30]	The ordered probit models	Older motorcyclists have been found to be significantly linked with more severe injuries.
Pai [9]	Binary logistic models	
Shaheed and Gkritza [15]	A latent class logit model	People over the age of 25 are at a higher risk of suffering severe injuries while riding.
Tamakloe et al. [35]	Binary logit models	young rider's behavior made it highly probable that casualty fatalities increase at non-signalized intersections.
Abrari Vajari et al. [33]	The multinomial logit model	Fatalities involving motorcyclists are more common among those over the age of 59.
Wang et al. [27]	A random parameter logit approach with heterogeneity in means and variances	Fatalities involving motorcyclists are more common among those over the age of 50.
Waseem et al. [36]	A random parameter logit approach with heterogeneity in means and variances	Fatalities involving motorcyclists are more common among those over the middle-aged of (25-50).

motorcyclists of various age groups is limited. For instance, Jung et al. [32] employed multinomial logit models to estimate injury severities of motorcyclists categorized by age group (under 25, 35-44, and 45-54), while Islam [29] utilized mixed logit models to examine the impact of three age groups (under 30, 30-49, and 50 and over) on motorcyclist outcomes, but only in the context of single-vehicle crashes.

To address this gap in the research literature, a random parameters logit model is estimated to examine the difference in contributing factors of injury severity involving motorcyclists of different age groups. To better understand the variation in the distribution of motorcyclist injury severity across age groups, the current study extensively carried out a series of out-of-sample predictive simulations. The findings from this paper are expected to help policymakers take necessary measures in reducing motorcyclists of different age groups by forming appropriate strategies and properly allocating their available resources at the pre-planning phase.

III. DATA DESCRIPTION

Four-year crash data from the UK were drawn from the STATS19 dataset [37]. The dataset comprises three files: accident file, vehicle file, and casualty file. In order to merge the three sub-sets, we utilized the accident and vehicle reference numbers that were provided for this study. After merging, the unit of analysis in the current paper is the accident. And each case contains the time/date of accident occurrence, weather, road, light conditions, posted speed limit, road type, age and gender the driver, vehicle type, first impact point of the vehicle, vehicles' maneuvers, and injury-severity level. A total of 10,437 multi-vehicle motorcycle crashes were extracted: Out of the total population, 38.00% belong to the under 25 age

TABLE 2. Distribution of significant variables across injury severity levels. [minor injury (MI), severe injury (SI), and fatal injury (FI)].

Variable Description	Age under 25			Age 25-55			Aged 55 and above		
	MI	SI	FI	MI	SI	FI	MI	SI	FI
Motorcyclist characteristics									
Male motorcyclist indicator (1 if male, 0 otherwise)	2518* (68.00%)	1150 (31.06%)	35 (0.95%)	3143 (63.60%)	1650 (33.39%)	149 (3.01%)	577 (52.84%)	461 (42.22%)	54 (4.95%)
Driver characteristics									
Male driver indicator (1 if male, 0 otherwise)	1581 (67.42%)	737 (31.43%)	27 (1.15%)	2010 (61.98%)	1118 (34.47%)	115 (3.55%)	375 (51.87%)	308 (42.60%)	40 (5.53%)
Middle-age driver indicator (1 if between 25 and 55 years, 0 otherwise)	1734 (66.59%)	839 (32.22%)	31 (1.19%)	2216 (62.69%)	1201 (33.97%)	118 (3.34%)	424 (52.67%)	342 (42.48%)	39 (4.84%)
Older driver indicator (1 if 55 years and above, 0 otherwise)	202 (61.77%)	122 (37.31%)	3 (0.92%)	221 (54.03%)	172 (42.05%)	16 (3.91%)	66 (50.38%)	56 (42.75%)	9 (6.87%)
Roadway and environmental conditions									
Weather condition indicator (1 if fine, 0 otherwise)	2234 (67.82%)	1027 (31.18%)	33 (1.00%)	2856 (62.60%)	1561 (34.22%)	145 (3.18%)	546 (52.40%)	444 (42.61%)	52 (4.99%)
Speed limit indicator (1 if 20 mph, 0 otherwise)	193 (82.13%)	42 (17.87%)	0 (0.00%)	358 (82.87%)	72 (16.67%)	2 (0.46%)	20 (80.00%)	5 (20.00%)	0 (0.00%)
Speed limit indicator (1 if 30 mph, 0 otherwise)	1937 (70.44%)	801 (29.13%)	12 (0.44%)	2094 (71.42%)	798 (27.22%)	40 (1.36%)	334 (65.11%)	171 (33.33%)	8 (1.56%)
Speed limit indicator (1 if 40 mph, 0 otherwise)	237 (65.47%)	122 (33.70%)	3 (0.83%)	332 (60.36%)	206 (37.45%)	12 (2.18%)	60 (50.00%)	57 (47.50%)	3 (2.50%)
Speed limit indicator (1 if 60 mph, 0 otherwise)	205 (51.51%)	176 (44.22%)	17 (4.27%)	370 (42.14%)	430 (48.97%)	78 (8.88%)	139 (38.83%)	183 (51.12%)	36 (10.06%)
Roundabout indicator (1 if roundabout, 0 otherwise)	204 (83.95%)	38 (15.64%)	1 (0.41%)	296 (77.89%)	84 (22.11%)	0 (0.00%)	70 (60.34%)	46 (39.66%)	0 (0.00%)
Single carriageway indicator (1 if single carriageway, 0 otherwise)	2176 (67.10%)	1033 (31.85%)	34 (1.05%)	2491 (62.28%)	1378 (34.45%)	131 (3.28%)	468 (52.17%)	380 (42.36%)	49 (5.46%)
Urban area indicator (1 if urban area, 0 otherwise)	2015 (70.78%)	819 (28.77%)	13 (0.46%)	2463 (73.00%)	871 (25.82%)	40 (1.19%)	309 (63.98%)	169 (34.99%)	5 (1.04%)
Motorcycle characteristics									
Motorcycle straight movement (1 if straight; 0 otherwise)	1627 (65.05%)	845 (33.79%)	29 (1.16%)	2023 (61.68%)	1133 (34.54%)	124 (3.78%)	345 (50.51%)	294 (43.05%)	44 (6.44%)
Newer motorcycle (1 if under 6 years old; 0 otherwise)	1437 (70.79%)	575 (28.33%)	18 (0.89%)	1521 (69.52%)	620 (28.34%)	47 (2.15%)	201 (53.46%)	160 (42.55%)	15 (3.99%)
Middle-age motorcycle (1 if between 6 and 11 years; 0 otherwise)	522 (64.68%)	282 (34.94%)	3 (0.37%)	613 (64.46%)	310 (32.60%)	28 (2.94%)	115 (59.28%)	65 (33.51%)	14 (7.22%)
Older motorcycle (1 if 11 years and above; 0 otherwise)	460 (60.29%)	292 (38.27%)	11 (1.44%)	882 (57.38%)	591 (38.45%)	64 (4.16%)	237 (52.43%)	198 (43.81%)	17 (3.76%)
Non-motorcycle vehicle characteristics									
Vehicle straight movement (1 if straight movement; 0 otherwise)	835 (62.78%)	471 (35.41%)	24 (1.80%)	1079 (56.55%)	726 (38.05%)	103 (5.40%)	224 (47.06%)	216 (45.38%)	36 (7.56%)
Middle-age vehicle (1 if between 6 and 11 years; 0 otherwise)	627 (68.30%)	282 (30.72%)	9 (0.98%)	713 (62.38%)	396 (34.65%)	34 (2.97%)	139 (54.94%)	105 (41.50%)	9 (3.56%)
Passenger car (1 if passenger car; 0 otherwise)	2280 (69.11%)	994 (30.13%)	25 (0.76%)	2807 (64.83%)	1416 (32.70%)	107 (2.47%)	504 (54.55%)	390 (42.21%)	30 (3.25%)
Truck (1 if truck; 0 otherwise)	249 (61.33%)	145 (35.71%)	12 (2.96%)	346 (59.35%)	201 (34.48%)	36 (6.17%)	63 (42.86%)	63 (42.86%)	21 (14.29%)

TABLE 2. ***(Continued.)*** **Distribution of significant variables across injury severity levels. [minor injury (MI), severe injury (SI), and fatal injury (FI)].**

Type of collision									
Head-on (1 if head-on; 0 otherwise)	810 (64.85%)	420 (33.63%)	19 (1.52%)	1119 (64.02%)	548 (31.35%)	81 (4.63%)	196 (52.83%)	143 (38.54%)	32 (8.63%)
Sideswipe (1 if sideswipe; 0 otherwise)	663 (71.75%)	259 (28.03%)	2 (0.22%)	634 (60.50%)	396 (37.79%)	18 (1.72%)	141 (55.08%)	105 (41.02%)	10 (3.91%)
Rear-end (1 if rear-ended; 0 otherwise)	1029 (68.24%)	464 (30.77%)	15 (0.99%)	1317 (65.04%)	661 (32.64%)	47 (2.32%)	222 (51.03%)	204 (46.90%)	9 (2.07%)
Temporal variables									
Morning off-peak indicator (1 if crash time is 10:00-12:00, 0 otherwise)	1163 (69.35%)	494 (29.46%)	20 (1.19%)	1514 (62.28%)	847 (34.84%)	70 (2.88%)	405 (51.86%)	335 (42.89%)	41 (5.25%)
Morning peak indicator (1 if crash time is 7:00-9:00, 0 otherwise)	406 (72.89%)	147 (26.39%)	4 (0.72%)	552 (68.40%)	239 (29.62%)	16 (1.98%)	81 (55.86%)	58 (40.00%)	6 (4.14%)
Evening off-peak indicator (1 if crash time is 20:00-24:00, 0 otherwise)	105 (65.22%)	55 (34.16%)	1 (0.62%)	160 (61.78%)	85 (32.82%)	14 (5.41%)	22 (59.46%)	14 (37.84%)	1 (2.70%)
Day of the week indicator (1 if Monday, 0 otherwise)	274 (66.99%)	131 (32.03%)	4 (0.98%)	388 (56.07%)	273 (39.45%)	31 (4.48%)	108 (49.54%)	98 (44.95%)	12 (5.50%)
Day of the week indicator (1 if Tuesday, 0 otherwise)	369 (68.59%)	159 (29.55%)	10 (1.86%)	430 (64.66%)	216 (32.48%)	19 (2.86%)	83 (60.14%)	49 (35.51%)	6 (4.35%)
Day of the week indicator (1 if Saturday, 0 otherwise)	433 (68.08%)	200 (31.45%)	3 (0.47%)	570 (62.43%)	317 (34.72%)	26 (2.85%)	85 (54.14%)	66 (42.04%)	6 (3.82%)
Season indicator (1 if Winter, 0 otherwise)	609 (70.00%)	249 (28.62%)	12 (1.38%)	825 (68.29%)	359 (29.72%)	24 (1.99%)	116 (67.44%)	53 (30.81%)	3 (1.74%)

* presented the descriptive statistics distribution of each variable across injury severity levels.

group, 50.90% belong to the 25-55 age group, and 11.10% belong to the 55 and above age group.

This study considers three levels of injury severity - minor, serious, and fatal injuries - based on the STATS19 injury classification. The dependent variable for the models is the injury-severity level, and the dataset does not include crashes that resulted in no injuries [38] (68.71%, 30.36%, and 0.93% for minor injury, serious injury, and fatal injury in young-age crashes, respectively; 64.33%, 32.79%, and 2.88% for minor injury, serious injury and fatal injury in middle-age crashes, respectively; and 53.37%, 41.97%, and 4.66% for minor injury, serious injury and fatal injury in older age crashes, respectively). Table 2 presents the descriptive statistics for the main variables in the injury severity models for multi-vehicle motorcycle crashes.

IV. METHODOLOGY

In this study, we utilize separate random parameters logit models to examine the factors affecting the injury severity of motorcyclists across various age groups. The first step involves specifying an injury severity function (denoted as Y_{in}) that determines the severity level of a motorcyclist's injury i in a given crash n [39], [40].

$$Y_{in} = \beta_{\mathrm{i}}\mathrm{X}_{\mathrm{in}} + \varepsilon_{in} \tag{1}$$

The explanatory variables that impact the severity of injuries suffered by motorcyclists involved in a crash (minor, severe, or fatal) are represented by the vector X_{in}. The corresponding estimable parameters are denoted by β_{i}, and the error term, ε_{in}, is assumed to follow an independent and identical distribution with zero mean and variance σ^2. Using a random parameters multinomial logit model, one can obtain the injury severity probabilities as in [34], [41], [42], and [43]:

$$P_n(i|\varphi) = \int \frac{\exp(\beta_{\mathrm{i}}\mathrm{X}_{\mathrm{in}})}{\sum_{i\in I}\exp(\beta_{\mathrm{i}}\mathrm{X}_{\mathrm{in}})} f(\beta_{\mathrm{i}}|\varphi)d\beta_{\mathrm{i}} \tag{2}$$

The expression $p_n(i|\varphi)$ denotes the probability of observing injury severity level i given the values of the random parameters β_{I}, represented by the density function $f(\beta_{\mathbf{i}}|\boldsymbol{\varphi})$, where φ is a vector of parameters (means and variances) that characterize the distribution of β_{I}.

To estimate the random parameters multinomial logit model, a simulated maximum likelihood method is employed, with 1,000 Halton draws used to achieve stable parameter estimates as reported in [44]. The normal distribution is adopted for the distribution of the random parameters to achieve the best goodness of fit, as noted in [43].

To provide a quantitative description of the impact of explanatory variables on the severity of injuries suffered by motorcyclists, we calculate pseudo-elasticities. In this paper, all variables used in the estimated models are binary indicator variables. The pseudo-elasticities are a measure of the change in the probability of the outcome (i.e., the severity of injuries) resulting from a change in an explanatory variable from "0" to "1," as stated in [39] and [43].

V. TEST FOR AGE GROUP DIFFERENCES

In order to investigate whether the parameters of motorcyclist injury severity in multi-vehicle motorcycle crashes are homogeneous across different age groups, we employed a modified version of the likelihood ratio test, as described in [39], [45], [46], [47], and [48]:

$$\chi^2 = -2\left[LL\left(\beta_{AllAge}\right) - LL\left(\beta_{Age<25}\right) - LL\left(\beta_{Age25-55}\right) - LL\left(\beta_{Age55+}\right)\right] \quad (3)$$

where, $LL\left(\beta_{AllAge}\right)$, $LL\left(\beta_{Age<25}\right)$, $LL\left(\beta_{Age25-55}\right)$, and $LL\left(\beta_{Age55+}\right)$ are the log-likelihood at the convergence from all age group data, young age group data, middle-aged group data, and older age group data, respectively.

To further examine whether the estimated parameters across age groups are the same, we conducted three pair-to-pair likelihood ratio tests [39]:

$$\chi^2 = -2\left[LL\left(\beta_{Age2Age1}\right) - LL\left(\beta_{Age1}\right)\right] \quad (4)$$

where, $LL\left(\beta_{Age2,Age1}\right)$ is the log-likelihood at the convergence derived from $Age2$'s data, while data derived from $Age1$, and $LL\left(\beta_{Age1}\right)$ is the log-likelihood at the convergence derived from $Age1$'s data. Table 3 presents the results of the null hypothesis that the parameters of any two age groups are stable. All the age groups were not equal, and the null hypothesis was rejected with more than 99% confidence, which is strong evidence that the estimated parameters vary with age groups. Therefore, in a multi-vehicle motorcycle crash, a separate model is needed to analyze the injury severity of motorcyclists in each age group.

TABLE 3. Comparison of the likelihood ratio test results for different age groups of motorcyclists (degrees of freedom in parentheses and confidence level in brackets).

$Age1$	$Age2$		
	Age under 25	Age 25-55	Age 55 and above
Age under 25	–	60.644 (30) [>99.92%]	141.972 (17) [>99.99%]
Age 25-55	112.645 (29) [>99.99%]	–	153.106 (17) [>99.99%]
Age 55 and above	186.070 (29) [>99.99%]	182.197 (30) [>99.99%]	–

VI. MODEL RESULTS

Table 4 displays the results of model estimation for multi-vehicle motorcycle crashes involving motorcyclists from various age groups. The evaluation of the models was based on three metrics: Akaike Information Criterion (AIC) value, McFadden R-Squared, and the log-likelihood value at convergence. A smaller AIC value, higher McFadden R-Squared value, and higher log-likelihood value at convergence indicate a better fit for the model [39], [49], [50], [51]. The goodness-of-fit measures suggest that the random parameters multinomial logit approach outperforms the multinomial logit approach for all analysis scenarios. Below, we discuss the estimated results by variable category.

A. INSIGHTS FROM RANDOM PARAMETERS

The model estimation results for the multi-vehicle motorcycle crashes involving motorcyclists of different age groups are shown in Table 4. For the aged under 25 model, there are four statistically significant variables as random parameters, including the constant term, truck-involved, rear-end collision, and morning off-peak hours indicator. Among them, the constant term specific to severe injury is a random parameter. The truck-involved indicator in the severe injury severity outcome is statistically significant as a random parameter, where 38.56% of the crashes increase the probability of severe injury (and the rest have a reduction). The rear-end collision indicator is also a significant random parameter, with a low probability of minor injury for 67.60% of the observations. The morning off-peak hours indicator in the minor injury severity outcome is statistically significant as a random parameter, where 66.68% of the crashes increase the probability of minor injury (and the rest have a reduction).

For the 25-55 model, there are two statistically significant variables as random parameters (see Table 4), including the constant term and straight movement. Among them, the constant term specific to severe injury is a random parameter. The straight movement indicator in the severe injury severity outcome is statistically significant as a random parameter, where 36.59% of the crashes increase the probability of minor injury (and the rest have a reduction).

For the aged 55 and above model, there are three statistically significant variables as random parameters (see Table 4), including the constant term, passenger car, and sideswipe. Among them, the constant term specific to severe injury is a random parameter. The passenger car indicator in the severe injury severity outcome is statistically significant as a random parameter, where 67.59% of crashes increase the probability of severe injury (and the rest have a reduction). The sideswipe collision indicator is also a significant random parameter, with a low probability of severe injury for 60.93% of the observations.

B. RIDER AND DRIVER_RELATED CHARACTERISTICS

As shown in Table 4, there is only one statistically significant rider-related variable in the young-age crashes model. The non-motorcycle driver-related characteristics, such as middle-aged drivers (between 25 and 55 years) and older drivers (55 years and above), also significantly affect motorcyclists' injury severity when considering multi-vehicle motorcycle crashes.

More specifically, the male indicator significantly increases the risk of a fatal injury of young motorcyclists

TABLE 4. Model results of motorcyclists' injury severity involving different age groups in multi-vehicle motorcycle crashes.

Variable	Aged under 25		Aged 25-55		Aged 55 and above	
	Parameter estimate	t-stat.	Parameter estimate	t-stat.	Parameter estimate	t-stat.
Constant [MI]	8.412	6.66	5.419	8.59	2.202	3.92
Constant [SI]	3.871	6.07	3.696	7.62	3.076	4.76
Standard Deviation of Parameter Density Function	3.525	3.18	2.942	3.56	3.135	2.68
Motorcyclist characteristics						
Male motorcyclist indicator (1 if male, 0 otherwise) [MI]	-1.448	-2.79	–	–	–	–
Driver characteristics						
Middle-age driver indicator (1 if between 25 and 55 years, 0 otherwise) [MI]	-1.221	-3.39	–	–	–	–
Older driver indicator (1 if 55 years and above, 0 otherwise) [MI]	-1.552	-3.31	-0.511	-2.34	–	–
Roadway and environmental conditions						
Weather condition indicator (1 if fine, 0 otherwise) [MI]	-0.515	-1.99	-0.857	-3.52	–	–
Speed limit indicator (1 if 20 mph, 0 otherwise) [MI]	2.657	3.26	2.625	4.42	4.387	2.79
Speed limit indicator (1 if 30 mph, 0 otherwise) [MI]	0.812	2.48	1.489	3.79	2.429	6.13
Speed limit indicator (1 if 40 mph, 0 otherwise) [MI]	–	–	0.530	2.16	1.188	2.57
Speed limit indicator (1 if 60 mph, 0 otherwise) [MI]	-0.996	-2.31	–	–	–	–
Roundabout indicator (1 if roundabout, 0 otherwise [MI]	2.507	3.45	–	–	–	–
Roundabout indicator (1 if roundabout, 0 otherwise [SI]	–	–	-0.842	-2.26	–	–
Single carriageway indicator (1 if single carriageway, 0 otherwise) [MI]	–	–	-0.821	-3.72	–	–
Urban area indicator (1 if urban area, 0 otherwise) [MI]	–	–	0.743	3.43	–	–
Motorcycle characteristics						
Motorcycle straight movement (1 if straight; 0 otherwise) [MI]	–	–	-1.001	-3.32	-0.689	-2.33
Motorcycle straight movement (1 if straight; 0 otherwise) [SI]	1.232	3.38	-0.664	-2.11	–	–
Motorcycle straight movement (1 if straight; 0 otherwise) [FI]	1.096	2.28	–	–	–	–
Newer motorcycle (1 if under 6 years old; 0 otherwise) [MI]	1.035	3.69	–	–	–	–
Newer motorcycle (1 if under 6 years old; 0 otherwise) [SI]	–	–	-0.467	-2.72	–	–
Middle-age motorcycle (1 if between 6 and 11 years; 0 otherwise) [MI]	1.368	3.54	–	–	–	–
Middle-age motorcycle (1 if between 6 and 11 years; 0 otherwise) [SI]	–	–	–	–	-1.619	-2.61
Older motorcycle (1 if 11 years and above; 0 otherwise) [SI]	-0.726	-2.30	–	–	–	–
Older motorcycle (1 if older than 11 years and above; 0 otherwise) [FI]	–	–	0.420	1.91	–	–
Non-motorcycle vehicle characteristics						
Vehicle straight movement (1 if straight; 0 otherwise) [MI]	-0.673	-2.75	-0.888	-3.43	–	–
Vehicle straight movement (1 if straight; 0 otherwise) [SI]	–	–	-0.696	-2.28	–	–
Standard Deviation of Parameter Density Function	–	–	2.030	2.27	–	–
Middle-age vehicle (1 if between 6 and 11 years; 0 otherwise) [MI]	–	–	-0.267	-1.81	–	–
Passenger car (1 if passenger car; 0 otherwise) [MI]	–	–	–	–	1.544	4.44
Passenger car (1 if passenger car; 0 otherwise) [SI]	–	–	–	–	1.497	2.78
Standard Deviation of Parameter Density Function	–	–	–	–	3.280	2.09
Truck (1 if truck; 0 otherwise) [MI]	-1.409	-3.16	-1.219	-3.96	–	–
Truck (1 if truck; 0 otherwise) [SI]	-1.810	-1.82	-1.031	-2.97	–	–
Standard Deviation of Parameter Density Function	6.225	2.06	–	–	–	–
Type of collision						
Head-on (1 if head-on; 0 otherwise) [MI]	-1.043	-2.96	–	–	-1.653	-4.82
Head-on (1 if head-on; 0 otherwise) [SI]	–	–	–	–	-2.089	-3.90
Sideswipe (1 if sideswipe; 0 otherwise) [SI]	–	–	–	–	-1.810	-1.81
Standard Deviation of Parameter Density Function	–	–	–	–	6.525	1.91
Sideswipe (1 if sideswipe; 0 otherwise) [FI]	–	–	-0.914	-2.70	–	–
Rear-end (1 if rear-end; 0 otherwise) [MI]	-0.644	-2.13	–	–	–	–
Standard Deviation of Parameter Density Function	1.411	1.80	–	–	–	–
Rear-end (1 if rear-ended; 0 otherwise) [FI]	–	–	-0.479	-2.06	–	–
Temporal variables						
Morning off-peak indicator (1 if crash time is 10:00-12:00, 0 otherwise) [MI]	0.678	2.36	–	–	–	–
Standard Deviation of Parameter Density Function	1.573	2.49	–	–	–	–
Morning peak indicator (1 if crash time is 7:00-9:00, 0 otherwise) [MI]	0.856	2.58	–	–	–	–
Evening off-peak indicator (1 if crash time is 20:00-24:00, 0 otherwise) [MI]	–	–	-0.751	-2.45	–	–
Day of the week indicator (1 if Monday, 0 otherwise) [MI]	–	–	-0.355	-1.96	–	–
Day of the week indicator (1 if Tuesday, 0 otherwise) [FI]	0.858	1.92	–	–	–	–
Day of the week indicator (1 if Saturday, 0 otherwise) [MI]	–	–	-0.306	-1.89	–	–
Season indicator (1 if Winter, 0 otherwise) [MI]	–	–	–	–	1.337	2.90
Model statistics						
Number of parameters (K)	29		30		17	
Number of observations (N)	3966		5313		1158	
Log-likelihood at zero	-4357.096		-5836.927		-1272.193	
Log-likelihood at convergence	-2448.372		-3655.949		-892.214	
ρ^2=1-LL(β)/LL (0)	0.438		0.374		0.299	
Akaike information criterion (AIC)	4954.7		7371.9		1818.4	
Bayesian information criterion (BIC)	5137.0		7569.2		1904.4	

TABLE 5. Comparison of pseudo-elasticities (%) of riders' age on injury severity in multi-vehicle motorcycle crashes.

Variable	Aged under 25			Aged 25-55			Aged 55 and above		
	MI	SI	FI	MI	SI	FI	MI	SI	FI
Motorcyclist characteristics									
Male motorcyclist indicator (1 if male, 0 otherwise) [MI]	-17.51	35.93	107.11	–	–	–	–	–	–
Driver characteristics									
Middle-age driver indicator (1 if between 25 and 55 years, 0 otherwise) [MI]	-10.78	20.54	62.77	–	–	–	–	–	–
Older driver indicator (1 if 55 years and above, 0 otherwise) [MI]	-1.98	3.09	9.39	-0.94	0.98	2.59	–	–	–
Roadway and environmental conditions									
Weather condition indicator (1 if fine, 0 otherwise) [MI]	-5.56	11.34	33.82	-14.10	21.10	53.52	–	–	–
Speed limit indicator (1 if 20 mph, 0 otherwise) [MI]	1.14	-5.46	-13.73	1.87	-8.99	-19.11	0.69	-2.76	-8.79
Speed limit indicator (1 if 30 mph, 0 otherwise) [MI]	6.56	-15.67	-45.76	10.39	-25.08	-43.98	14.00	-23.35	-93.61
Speed limit indicator (1 if 40 mph, 0 otherwise) [MI]	–	–	–	1.09	-1.52	-4.06	2.32	-2.00	-9.99
Speed limit indicator (1 if 60 mph, 0 otherwise) [MI]	-2.18	1.92	6.52	–	–	–	–	–	–
Roundabout indicator (1 if roundabout, 0 otherwise [MI]	1.02	-5.60	-13.54	–	–	–	–	–	–
Roundabout indicator (1 if roundabout, 0 otherwise [SI]	–	–	–	0.61	-2.20	0.66	–	–	–
Single carriageway indicator (1 if single carriageway, 0 otherwise) [MI]	–	–	–	-12.03	17.68	44.57	–	–	–
Urban area indicator (1 if urban area, 0 otherwise) [MI]	–	–	–	6.20	-16.20	-38.04	–	–	–
Motorcycle characteristics									
Motorcycle straight movement (1 if straight; 0 otherwise) [MI]	–	–	–	-12.35	17.40	44.01	-9.52	6.33	31.09
Motorcycle straight movement (1 if straight; 0 otherwise) [SI]	-9.81	19.98	-13.36	6.26	-12.18	6.54	–	–	–
Motorcycle straight movement (1 if straight; 0 otherwise) [FI]	-1.06	-0.34	65.74	–	–	–	–	–	–
Newer motorcycle (1 if under 6 years old; 0 otherwise) [MI]	6.24	-14.83	-43.05	–	–	–	–	–	–
Newer motorcycle (1 if under 6 years old; 0 otherwise) [SI]	–	–	–	2.48	-6.47	2.66	–	–	–
Middle-age motorcycle (1 if between 6 and 11 years; 0 otherwise) [MI]	2.57	-7.21	-20.45	–	–	–	–	–	–
Middle-age motorcycle (1 if between 6 and 11 years; 0 otherwise) [SI]	–	–	–	–	–	–	2.86	-6.23	2.86
Older motorcycle (1 if 11 years and above; 0 otherwise) [SI]	1.50	-3.29	2.10	–	–	–	–	–	–
Older motorcycle (1 if 11 years and above; 0 otherwise) [FI]	–	–	–	-0.64	-0.21	10.46	–	–	–
Non-motorcycle vehicle characteristics									
Vehicle straight movement (1 if straight; 0 otherwise) [MI]	-3.48	5.41	17.13	-7.11	7.41	21.53	–	–	–
Vehicle straight movement (1 if straight; 0 otherwise) [SI]	–	–	–	2.62	-2.70	2.53	–	–	–
Middle-age vehicle (1 if between 6 and 11 years; 0 otherwise) [MI]	–	–	–	-1.11	1.65	4.17	–	–	–
Passenger car (1 if passenger car; 0 otherwise) [MI]	–	–	–	–	–	–	22.33	-20.67	-100.85
Passenger car (1 if passenger car; 0 otherwise) [SI]	–	–	–	–	–	–	-18.22	29.13	-18.22
Truck (1 if truck; 0 otherwise) [MI]	-1.66	1.92	11.39	-3.05	3.66	8.58	–	–	–
Truck (1 if truck; 0 otherwise) [SI]	0	0.38	0.95	1.74	-3.4	1.75	–	–	–
Type of collision									
Head-on (1 if head-on; 0 otherwise) [MI]	-4.88	8.51	26.31	–	–	–	-14.04	9.99	38.92
Head-on (1 if head-on; 0 otherwise) [SI]	–	–	–	–	–	–	9.05	-14.71	9.05
Sideswipe (1 if sideswipe; 0 otherwise) [SI]	–	–	–	–	–	–	1.19	-1.08	1.19
Sideswipe (1 if sideswipe; 0 otherwise) [FI]	–	–	–	0.40	0.14	-16.56	–	–	–
Rear-end (1 if rear-end; 0 otherwise) [MI]	-4.13	8.74	56.04				–	–	–
Rear-end (1 if rear-ended; 0 otherwise) [FI]	–	–	–	0.54	0.18	-16.56	–	–	–
Temporal variables									
Morning off-peak indicator (1 if crash time is 10:00-12:00, 0 otherwise) [MI]	1.99	-3.67	31.47	–	–	–	–	–	–
Morning peak indicator (1 if crash time is 7:00-9:00, 0 otherwise) [MI]	1.32	-3.50	-10.34	–	–	–	–	–	–
Evening off-peak indicator (1 if crash time is 20:00-24:00, 0 otherwise) [MI]	–	–	–	-0.76	1.00	2.53	–	–	–
Day of the week indicator (1 if Monday, 0 otherwise) [MI]	–	–	–	-1.06	1.17	3.13	–	–	–
Day of the week indicator (1 if Tuesday, 0 otherwise) [FI]	-0.26	-0.09	10.87				–	–	–
Day of the week indicator (1 if Saturday, 0 otherwise) [MI]	–	–	–	-1.01	1.51	3.81	–	–	–
Season indicator (1 if Winter, 0 otherwise)	–	–	–	–	–	–	2.53	-4.45	-17.33

by 107.11% on average (See Table 5). Young male motorcyclists generally have an increased risk of severe injury and fatal injury, and similar results were found in previous studies [5], [30]. A possible explanation may be that most young male motorcyclists (under 25 years) tend to be overconfident in their driving skills and are more likely to exhibit improper actions (such as aggressive driving or drunk driving) [45], resulting in severe injury. More enforcement and education programs about young male motorcyclists should be enhanced. In addition, when a motorcycle collides with another non-motorcycle vehicle, the middle-aged rider (between 25 and 55 years) indicator is associated with a decreased risk of minor injury, and the older driver (55 years and above) indicator reduces the risk of minor injury for young and middle-aged motorcycle riders. This result is not consistent with the existing research. Pai [9] concluded that elderly motorists (over 60 years) predisposed riders to a greater risk of injuries. One possible explanation: the brain, much like the body, declines with age, especially poor eyesight of the elderly may lead to their failure to detect the

motorcycle in time during driving, resulting in a collision; the reaction lag is also more likely to lead to severe injury crashes. Unlike motorized road users, due to the relative lack of protection in the event of a crash, motorcyclists tend to have higher rates of fatality and injury compared to other modes of transportation. But on the other hand, the driving skills and ability to rapid response to accidents also increase with age; therefore, the injury severity of the middle-aged above is relatively low.

C. RIDMOTORCYCLE AND NON-MONTORCYCLE CHARACTERISTICS

As shown in Table 4, some vehicle-related variables, including vehicle running status preceding collision, age of the vehicle, and non-motorcycle vehicle type, have a statistically significant effect on motorcyclists' injury severity.

More specifically, the straight movement of the motorcycle indicator reduces the risk of minor injury for middle-aged and elderly motorcyclists. Still, it increases the risk of serious injury and fatal injury for young motorcyclists by 19.98% and 65.74% (See Table 5). The possible explanation is that young motorcyclists are more likely to tempt drivers to speed when going straight. Excessive speed leads to greater collision kinetic energy, which greatly increases the risk of severe injury and fatal injury. It should be noted that the straight movement of non-motorcycle vehicle indicator reduces the risk of minor injury for young motorcyclists and middle-aged motorcyclists, and 63.41% of observations reduces the risk of minor injury for middle-aged motorcyclists (and in an increase in the rest 36.59%). A new motorcycle (under 6 years) reduces the probability of severe injury for middle-aged motorcyclists while increasing the probability of minor injury for young motorcyclists. Regularly performing maintenance checks on motorcycles, such as inspecting the chain, tires, and turning indicators, is crucial for preventing unexpected crashes. Therefore, it is recommended to prioritize and carry out appropriate maintenance work on motorcycles. Middle-aged motorcycle (between 6 and 11 years) reduces the probability of severe injury for older motorcyclists while increasing the probability of minor injury for young motorcyclists. Older motorcycle (11 years and above) reduces the probability of minor injury for young motorcyclists while increasing the estimated odds of fatal injuries involving middle-aged motorcyclists by 10.46%. It should be noted that the middle-aged non-motorcycle vehicle (between 6 and 11 years) indicator reduces the probability of minor injury for middle-aged motorcyclists. For young and middle-aged motorcyclists, being involved in an accident with a truck reduces the risk of both minor and severe injuries, whereas being involved in an accident with a passenger car increases the risk of such injuries for older motorcyclists.

D. ROADWAY AND ENVIROMENTAL CONDITIONS

As shown in Table 4, some roadway and environment-related variables, including weather conditions, speed limit, and road type, have a statistically significant effect on motorcyclists' injury severity.

More specifically, fine weather reduces the probability of minor injury for young and middle-aged motorcyclists. It should be noted that speed limit (20 mph) and speed limit (30 mph) are not transferable variables; namely, reducing the probability of minor injury for all aged-group motorcyclists while reducing the probability of severe injury and fatal injury. Middle-aged and older motorcyclists have a higher probability of sustaining minor injuries in accidents that occur at 40 mph. In contrast, young motorcyclists are more likely to suffer severe or fatal injuries at speeds of 60 mph, despite a lower probability of minor injuries. These findings suggest that higher speed limits in multi-vehicle motorcycle accidents are associated with greater injury severity. Similar results have been reported in previous studies [6], [9], [13], [16], [28], [30], [36]. Due to the location of the accident at the roundabout, the risk of severe injury is mitigated for middle-aged motorcyclists while younger motorcyclists are more likely to experience minor injuries. Young drivers are more likely to overspeed and run a stop light in the roundabout, resulting in severe injury and fatal injury after a collision with non-motorcycle vehicles. More enforcement and education programs about young motorcyclists should be enhanced. In addition, traffic wardens at the roundabout are responsible for enforcing the law relating to illegal parking. The accident happened in the single carriageway. The risk of minor injury is reduced for middle-aged motorcyclists while increasing the probability of severe injury and fatal injury (See Table 5). The possible reason is that single-lane roads are narrowly restricted by terrain and geological conditions, and the pathway has potential safety hazards. On the other hand, drivers driving the single-lane road usually do not need to pay attention to the vehicles on the opposite side, and motorcyclists may ride at a fast speed. Hence, they are prone to rear-end collisions with the vehicles in front of them. The probability of severe injury or fatal accidents is higher when the collision kinetic energy is greater. On urban roadways, the risk of minor injury is increased for middle-aged motorcyclists, while decreases the probability of severe injury and fatal injury for middle-aged motorcyclists (See Table 5). The results may be attributed to the greater availability of healthcare services in urban areas compared to rural areas [16].

E. CRASH-RELATED CHARACTERISTICS

As shown in Table 4, some crash-related variables, including head-on collision, sideswipe collision, and rear-end collision, have a statistically significant effect on motorcyclists' injury severity.

More specifically, the head-on collision indicator reduces the probability of minor injury for young motorcyclists and decreases the probability of minor and severe injury for older motorcyclists. The rear-end collision indicator reduces the probability of minor injury for young motorcyclists and decreases the probability of fatal injury for middle-aged motorcyclists. The sideswipe collision indicator

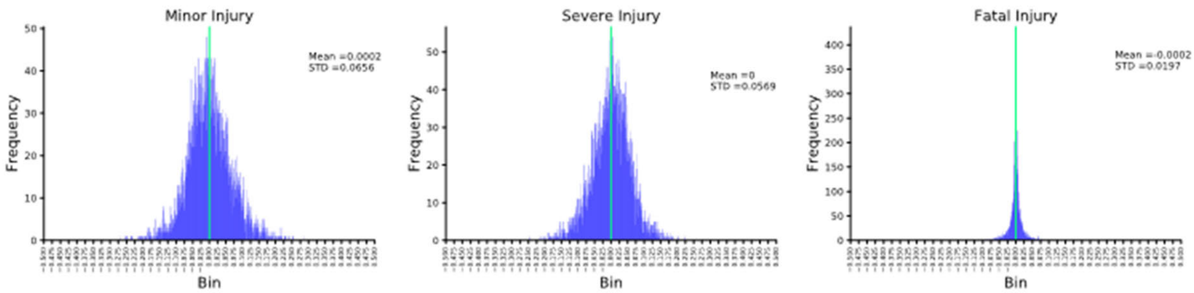

FIGURE 1. **Young age groups predict middle-age groups.**

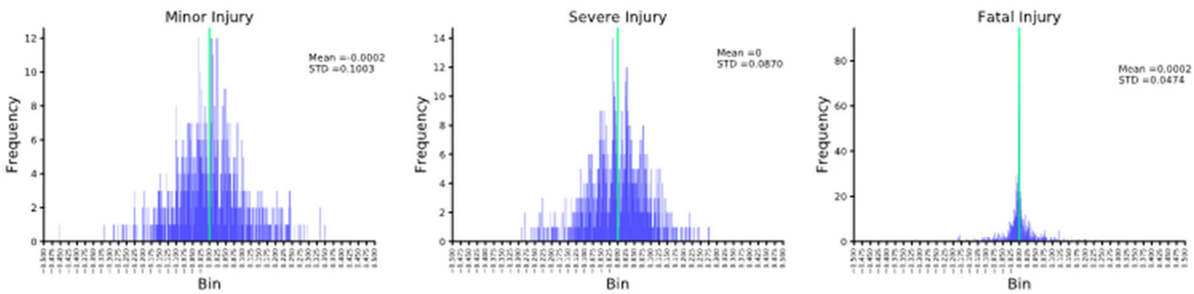

FIGURE 2. **Young age groups predict older age groups.**

reduces the probability of fatal injury for middle-aged motorcyclists. However, it should be noted that in 39.09% of observations, the sideswipe collision indicator significantly increases the probability of severe injury for older motorcyclists (see Table 4). This result appears to contradict existing research, which generally suggests that higher energy dissipation resulting from motor vehicles traveling towards each other is likely to contribute to more severe injury outcomes [16]. Pai and Saleh [6] and Su et al. [46] found that rear-end or sideswipes collision increase motorcyclists' injury severity. However, unlike head-on or rear-end collisions with large buffer zones, the relatively small buffer space on both sides of the vehicle is difficult to absorb kinetic energy to protect the occupant in a side impact. In addition, the main reason may be that the impact of the hit vehicle was on the side, meaning that at least one driver did not pay attention to oncoming traffic in the other direction. Hence, a high-speed collision is more likely to result in severe injury.

F. TEMPORAL-RELATED CHARACTERISTICS

As shown in Table 4, some temporal-related variables, including morning peak hours, day of the week, and season, have a statistically significant effect on motorcyclists' injury severity.

More specifically, the multi-vehicle motorcycle accident that happened during the morning rush hour increased the risk of minor injury for young motorcyclists. This finding also reveals the trip rules of commuters to a certain extent. There are more commuters in the morning rush hour, which is easy to cause traffic jams. Motorcyclists ride slower, resulting in minor injury accidents such as scratching. The fact that the collision occurred on Saturday reduces the risk of minor injury for middle-aged motorcyclists. Still, it increases the risk of severe injury and even fatal injury for middle-aged motorcyclists. Many motorcyclists will choose to go out on weekends or holidays, and many sensation-seekers will usually choose to ride relatively remote paths; In addition, some motorcyclists may like to use a weekend trip up straightway roads to test the limits of their motorcycle or to challenge their driving skills and abilities, which may be the reason for the high risk for motorcyclists on weekends. In Winter, the likelihood of minor injury is significantly increased for older motorcyclists. The conclusion is also intuitively easy to understand, during the Winter, low temperatures, alongside snow and ice on the road, will likely result in poor pavement friction, resulting in higher injury severities.

VII. MODEL RESULTS

The results of the above model and the discussion indicate that the influencing factors of motorcyclists' injury severity are transferable in different age groups. To further verify the transferability of influencing factors, this paper adopts the cross-validation method; namely, the influencing factors of the injury severity of motorcyclists involving the one age group crash are used to predict the probability of the injury severity of motorcyclists involving the other age group crash, and vice versa. Then the prediction accuracy is finally obtained by comparing the difference with the predicted

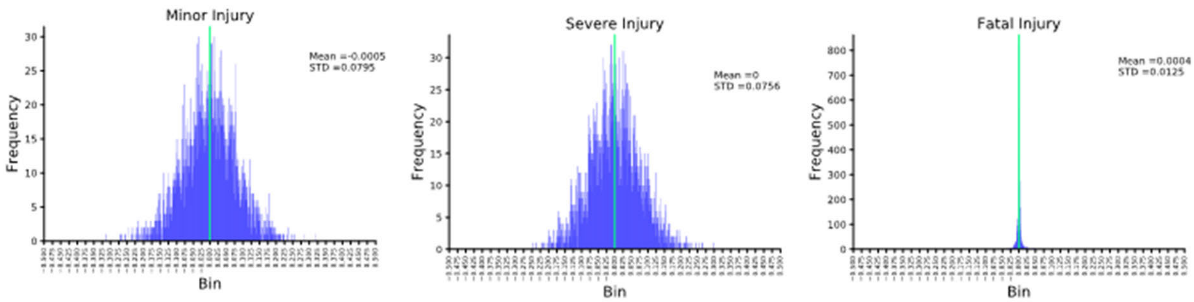

FIGURE 3. Middle-age groups predict young age groups.

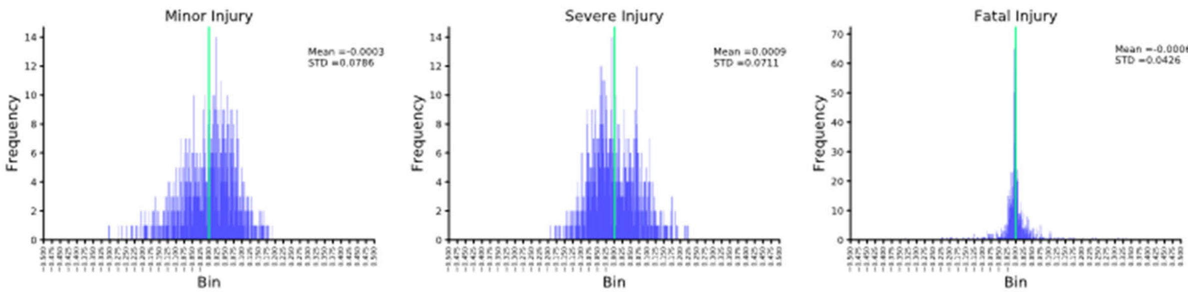

FIGURE 4. Middle-age groups predict older age groups.

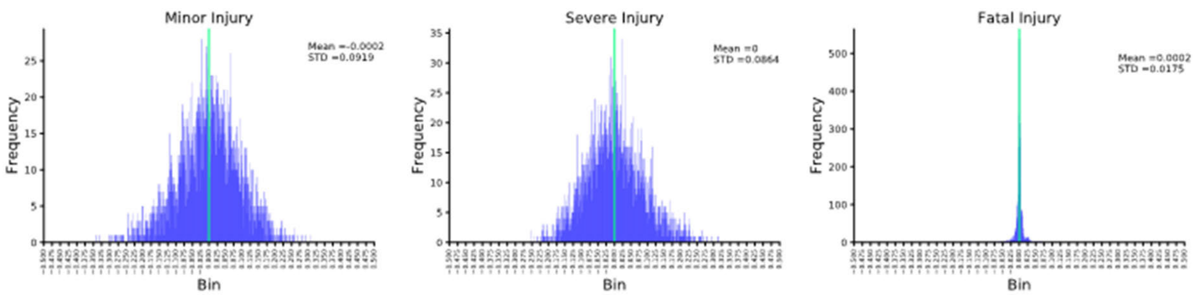

FIGURE 5. Older age groups predict young age groups.

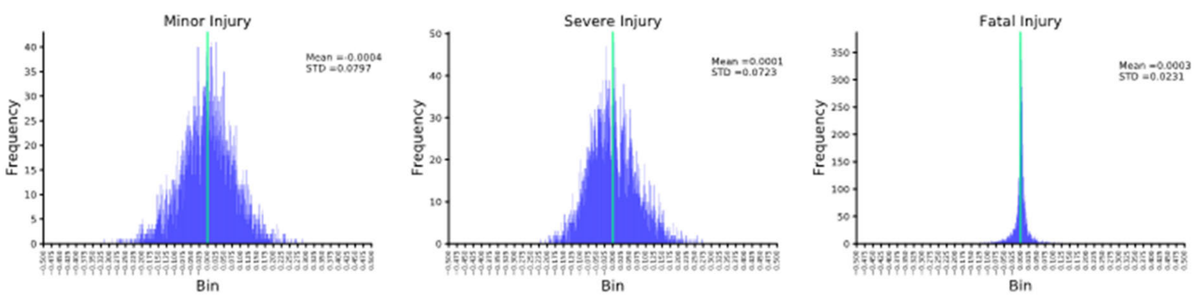

FIGURE 6. Older age groups predict middle-age groups.

probability of their influencing factors. The cross-validation method described above is called out-of-sample in statistics. Highlighting the significance, it must be acknowledged that the out-of-sample predictions do not rely on a mere average of random parameters, as such an approach would yield evidently biased results. For details on this technique, readers are referred to recent studies on the severity of injuries [19], [20], [21], [22], [23], [46].

First, we use the aged under 25 crash model to predict the injury severity of motorcyclists involving aged 25-55 given the observed motorcyclists involved aged between 25-55 crash characteristics. The results indicate that minor injury predictions are only overestimated by 0.0002. Fatal injury predictions are underestimated by 0.0002. The severe injury predictions have a stable difference. It seems that the influence factors of injury severity involving young motorcyclists can be used to predict middle-aged motorcyclists. Still, we also found that many individuals showed the prediction precision of the large deviation; namely, the mean value of prediction accuracy is likely to be the positive and negative balance between the high estimate and the low estimate in individual prediction. Therefore, judging the transferability of influencing factors only from the forecast mean value is defective. In order to express individual differences in the forecasting process more intuitively, this paper constructed the frequency distribution map of individual prediction accuracy. See Figure 1 for details. As shown in Figure 2, examining the use of the aged under 25 crash model to predict injury severity of motorcyclists involving aged 55 and above given the observed motorcyclists involving aged 55 and above crash characteristics. The results indicate that minor injury predictions are only underestimated by 0.0002. Fatal injury predictions are overestimated by 0.0002. The severe injury predictions also have a stable difference.

Second, examining the use of the aged between 25-55 crash model to predict the injury severity of motorcyclists involving aged under 25 given the observed motorcyclists involving aged under 25 crash characteristics. The results indicate that minor injury predictions are only underestimated by 0.0005 (See Figure 3). Fatal injury predictions are overestimated by 0.0004. The severe injury predictions have a stable difference. As shown in Figure 4, examining the use of the aged between 25-55 crash model to predict injury severity of motorcyclists involving aged 55 and above given the observed motorcyclists involving aged 55 and above crash characteristics. The results indicate that minor injury predictions are only underestimated by 0.0003. Fatal injury predictions are underestimated by 0.0006. Severe injury overestimated by 0.0009.

Third, examining the use of the aged 55 and above crash model to predict the injury severity of motorcyclists involving aged under 25 given the observed motorcyclists involving aged under 25 crash characteristics. The results indicate that minor injury predictions are only underestimated by 0.0002 (See Figure 5). Fatal injury predictions are overestimated by 0.0002. The severe injury predictions have a stable difference. As shown in Figure 6, examining the use of the aged 55 and above crash model to predict injury severity of motorcyclists involving aged between 25 and 55 given the observed motorcyclists involving aged between 25 and 55 crash characteristics. The results indicate that minor injury predictions are only underestimated by 0.0004. Fatal injury predictions are overestimated by 0.0002. Severe injury overestimated by 0.0003.

Like the research conducted by Yan et al. [25], it is pertinent to mention that this paper also exhibits relatively minor prediction deviation. Nonetheless, other studies have demonstrated considerable instances of underestimation and overestimation in their out-of-sample predictions [19], [21], [27].

VIII. CONCLUSION

This study employs four-year crash data from the UK to construct a random parameters logit model aimed at analyzing the severity of injuries sustained by motorcyclists across various age groups. The resultant models reveal a diverse range of factors - encompassing the riders, vehicles, roads, and environmental attributes - that have an impact on the severity of motorcyclists' injuries. The key findings are summarized as follows:

(1) The modeling outcomes indicated notable dissimilarities in the significant factors that influence crashes across three age groups, including rider characteristics, motorcycle and non-motorcycle characteristics, roadway and environmental conditions, temporal-related characteristics, and crash-related characteristics.

(2) The model results additionally indicate the presence of unobserved heterogeneity for three variables that are statistically significant, including the truck-involved, rear-end collision, and morning off-peak hours indicator in the under 25 age group crash model, and vehicle straight movement in the 25-55 age group crash model, and passenger car and sideswipe in the 55 above age group crash model.

(3) Furthermore, the results of the prediction comparison - conducted through an out-of-sample prediction simulation - clearly demonstrate significant differences in the likelihood of injury severity for motorcyclists belonging to various age groups. The findings from this analysis also offer a number of practical implications. First, this study untangled the multilayered role of unobserved heterogeneity in motorcyclists involving different age-group crashes. By analyzing the factors that affect injury severity among motorcyclists belonging to different age groups, decision makers can obtain comprehensive insights into the matter and develop more reasonable countermeasures to reduce the level of injury severity. Second, this study revealed different effects of explanatory variables on different age-group crashes. The results from this study are expected to help policymakers take necessary measures to reduce the injury severity of motorcyclists involving different age groups by forming appropriate strategies and properly allocating their available resources during the pre-planning phase.

In addition to the comprehensive analysis, we confirmed that the mechanisms affecting severity of injuries in age-group motorcycle crashes differ significantly. As the result, specific lesson learned from this study are as follows:

1) Young male motorcyclists (under 25 years) tend to be overconfident in their driving skills and are more likely to exhibit improper actions (such as aggressive driving or drunk driving), resulting in severe injury. More enforcement and education programs about young male motorcyclists

should be enhanced. 2) Regularly performing maintenance checks on motorcycles, such as inspecting the chain, tires, and turning indicators, is crucial for preventing unexpected crashes. Therefore, it is recommended to prioritize and carry out appropriate maintenance work on motorcycles. 3) Higher speed limits increase injury severity in motorcycle-involved accidents. To deal with this, motorcyclists who often riding on roads with high-speed limits should be required to wear safety gears and keep more space with other vehicles. 4) Attention should be paid to exercise where side impacts are likely- when a car might run into the side of motorcycle when it pulling over, for instance – encourage manufactures to widely deploy the Lane Change Alert with Side Blind Zone Alert system in their vehicles.

This study also has some limitations. Firstly, the interaction between gender and age can be considered. Secondly, a comparative study was conducted between single-vehicle and multiple-vehicle motorcycle crashes. Lastly, more multi-vehicle motorcycle crash datasets should be included in the future to investigate the temporal stability, and then to help policy makers to take necessary measures in reducing motorcycle involved crashes by forming appropriate and time-efficient strategies.

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YU HUANG was born in Fujian, China, in 1985. He received the B.S. and M.S. degrees from Beijing Jiaotong University, in 2008 and 2010, respectively. He is currently a Senior Engineer with China Communications Information Technology Group Company Ltd. His current research interests include urban intelligent transportation planning, intelligent transportation, and transportation information engineering.

YANYING WANG was born in Hebei, China, in 1986. She received the B.S. degree from the China University of Petroleum (East China), in 2008, and the M.S. degree in cartography and geographic information systems from the University of Chinese Academy of Sciences, in 2011. She is currently a Senior Engineer with China Communications Information Technology Group Company Ltd. Her current research interests include parallel image processing, intelligent transportation, and transportation information engineering.

LE TIAN was born in Shandong, China, in 1996. He received the B.S. degree in traffic engineering from the Inner Mongolia University of Technology, in 2018, and the M.S. degree in system science from Beijing Jiaotong University, in 2021. He is currently an Assistant Engineer with China Communications Information Technology Group Company Ltd. His current research interests include intelligent traffic, urban railway optimization, and the modeling of complex traffic and transportation systems.

CHUNHUI ZHANG was born in Heilongjiang, China, in 1986. He received the B.S. degree in logistics management from Beijing Wuzi University and the M.S. degree in intelligent transportation engineering from Beijing Jiaotong University, in 2013. He is currently a Senior Engineer with North China Municipal Engineering Design and Research Institute Company Ltd. His current research interests include urban intelligent transportation planning, intelligent transportation, and transportation information engineering.