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Alternative outcome frameworks to model injury severity outcomes of motorcyclists colliding with other vehicles

Dongdong Song^a, Chenzhu Wang^b, Said M. Easa^c, Renteng Yuan^d, Fei Chen^b, Jianchuan Cheng^b, Yitao Yang^e and Le Tian^f

^aSchool of Automobile, Chang'an University, Xi'an, China; ^bSchool of Transportation, Southeast University, Nanjing, Jiangsu, China; ^cDepartment of Civil Engineering, Toronto Metropolitan University Toronto, Ontario, Canada; ^dCollege of Automobile and Traffic Engineering, Nanjing Forestry University, Nanjing, Jiangsu, P. R. China; ^eDepartment of Transport & Planning, Faculty of Civil Engineering and Geosciences Delft University of Technology, Delft, The Netherlands; ^fChina Communications Information Technology Group Co. Ltd., Beijing, China

ABSTRACT

Lacking protection compared to drivers of other vehicles, motorcyclists accounted for most casualties and fatalities. This study explores how non-motorcycle drivers affect motorcyclists' injury outcomes in motorcycle-vehicle collisions. The motorcycle-vehicle crashes from the United Kingdom for 2016–2020 are used to estimate two alternative logit models to account for possible unobserved heterogeneities. The models are a latent class multinomial logit with class probability functions and a random threshold-parameter generalized ordered logit. With three possible injury severity levels (fatal injury, severe injury, and minor injury), the characteristics of motorcyclist, driver, roadway, environment, vehicle, and collision are considered potential determinants. Then, the temporal instability issues are revealed through the likelihood ratio tests and out-of-sample predictions based on the two models. Showing good ρ^2 values of over 0.370, the latent class model's estimation results are leveraged to quantify the effects of the contributing factors. Moreover, the marginal effects are also calculated to reveal the existing temporal instability, while some variables reflect the temporal instability in the influence trend and degree. The critical factors increasing the risk levels are male motorcyclists, higher speed limit, older ages of motorcyclists and vehicles, fine weather, single carriageway, and head-on collision type. Overall, subtle variations in the injury severity predictions exist in alternative heterogeneity modeling approaches, suffering from the modeling mechanism of different structural frameworks in capturing the unobserved heterogeneities.

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Temporal stability; motorcycle-vehicle crashes; injury severity; latent class model; generalized ordered model; unobserved heterogeneity

Introduction

Worldwide, motorcyclists are among the most vulnerable road users, including pedestrians and cyclists, who made up about half of the 1.35 million fatalities that resulted from traffic road crashes in 2016 (WHO 2018). For example, in the UK, motorcyclists made up 19.2% and 12.3% of the total fatalities and casualties caused by all traffic crashes in 2021, respectively, while the reported motorcyclists' fatality and causality number increased by 5% and 16% from 2020 (Department for Transport Statistics 2021). The exacerbated circumstance has become a significant public health concern, and more efforts should be devoted to implementing effective injury mitigation policies for motorcyclists.

Many researchers have studied motorcycle crashes (Chang et al. 2019; Islam 2021; Li et al. 2021; Se et al. 2022; Wang, Ijaz, et al. 2022). However, only a few studies have focused on motorcycle crashes colliding with other vehicles, but the characteristics of other vehicles were often neglected. In addition, temporal instability has gained fruitful findings in recent studies, while significant risk factors might vary over time, affected by the changes in characteristics of humans, vehicles, traffic, and economic conditions (Mannering 2018). Otherwise, a detailed review discussed by (Mannering, Shankar, and Bhat 2016) reviewed the unobserved heterogeneity along with the models proposed to capture it. Numerous previous studies have captured the temporal instability and unobserved heterogeneity in motorcycle crash severity analysis based on heterogeneity modeling approaches (Alnawmasi and

Mannering 2019; Se et al. 2022; Wang, Chen, et al. 2024). Recent studies provided substantial evidence that ignoring temporal effects and unobserved heterogeneity might cause biased estimation results and incorrect conclusions. Among the models addressing unobserved heterogeneity, a distribution (normal, uniform, lognormal, logistics, and triangular) is assumed to be random parameters, which can vary across observations by capturing heterogeneity in means and variances (Behnood and Mannering 2017; Wang, Chen, Zhang, and Cheng 2022; Wang, Chen, Zhang, Wang, et al. 2022; Washington et al. 2020; Wang, et al. 2024a). However, without a heterogeneity distribution assumption, latent class models can accurately track the unobserved heterogeneities in the data by grouping the crash data into homogeneous subsets across observations (Mohamed et al. 2013). By identifying two or more latent classes, the latent class multinomial logit model with class probability functions will be utilized in the current study to gain new insights into the potential associations, such as the characteristics of non-motorcycle drivers and motorcyclists. Shaheed and Gkritza (2014) identified two distinct classes of crashes based on a latent class multinomial logit model. Behnood, Roshandeh, and Mannering (2014) also found two latent class models that capture unobserved heterogeneity. Except for the unordered framework, the ordered logit models can also be assumed to link to continuous latent elements (Fountas and Anastasopoulos 2017; Washington et al. 2020; Yu, Ma, and Shen 2021). In addition, by capturing the

unobserved heterogeneity in the parameters and the thresholds, the random thresholds random parameters generalized ordered logit model has been developed in recent crash severity research (Mannering, Shankar, and Bhat 2016). Eluru and Yasmin (2015) indicated that the general ordered logit model variant offers enhanced model specification and estimation framework in capturing unobserved heterogeneities due to its parameterization structure. Moreover, Yasmin et al. (2014) and Marcoux et al. (2018) also developed an extension of the ordered logit model to provide more robust results for crash severity outcomes.

To the authors' best knowledge, a limited body of research efforts has produced robust estimation results through comparisons of alternative logit models by comparing the unordered and ordered frameworks in terms of estimation results, marginal effects, and temporal instability. While both latent class models and ordered logit models have been demonstrated to capture unobserved heterogeneity, further analysis is necessary to address the current research gap in understanding the differing interpretability of these two model structures.

Due to the complexity of the issues concerning the motorcyclists that collided with non-motorcycles, the structure of unobserved heterogeneities might be more complex than those in overall two-motorcycle crashes. Therefore, to capture the unobserved heterogeneity and allow assessing the temporal effects, two heterogeneity models are applied in this paper: a latent class multinomial logit with class probability functions (LCMLCP) model and a random thresholds-parameters generalized ordered logit (RTRPGOL) model.

Thus, to assess motorcyclists' safety policies, the current study presents a novel understanding of the temporal instability in motorcycle crashes to better understand the effects of the related elements of other vehicles by capturing the potential heterogeneous effects. Specifically, the purpose of the study is fourfold: (1) to collect driver and vehicle attributes of other vehicles that collided with motorcycles using data from the UK across 2016–2020, (2) to reveal the similarities/differences in the LCMLCP and RTRPGOL models when addressing unobserved heterogeneity, (3) to examine the variations in motorcyclist injury severities across years based on a robust temporal instability analysis using unobserved-heterogeneity models, and (4) to compare the marginal effects of the determinants by conducting out-of-sample predictions to depth reveal the changes in injury severities varying by years.

Given this, this paper comprehensively estimates the injury severities of motorcyclists based on advanced heterogeneity

approaches when colliding with other vehicles. Figure 1 presents the research flow chart. The two heterogeneity models and collected data are described, followed by the likelihood ratio tests and out-of-sample predictions. Then, the estimation results are discussed. Finally, the summaries and conclusions are presented. Specifically, motorcycle-vehicle crashes are estimated in terms of specific years based on the motorcyclist, driver, roadway, environmental, vehicle, and temporal characteristics. Other than the differences in the performance of the two methodological approaches estimated in this study, the significant factors and temporal instability are also addressed in this paper. Then, several valuable and robust findings from a long-term perspective can be revealed to implement some practical applications.

Data description

Table 1 shows the motorcycle-vehicle crash data in the UK from 2016 to 2020 collected from the STATS19 dataset (Department for Transport Statistics 2021). As noted in Figure 2, considerable differences existed in the injury severity number and distribution across the five years. The number of motorcycle-vehicle crashes decreased within two-year periods, including 2016–2017 and 2018–2019. However, the number climbs from 1872 in 2019 to 2296 in 2020, while fatal injury outcomes account for more proportions from 2018 to 2020 (from 1.0% to 3.0%). Such a phenomenon could be explained by the impact of the COVID-19 pandemic on traffic safety (Wang, Abdel-Aty, and Han 2024), while Alhajyaseen et al. (2022) observed that the crash rate increased even with a reduction in vehicle mileage traveled and rates of fatal injuries per 1000 crashes also increased (Doucette et al. 2021). Thus, more attention should be paid, and more effective countermeasures should be implemented to eliminate the injury severity outcomes of motorcyclists.

Table 2 provides the summary statistics for the variables in motorcycle crashes across the five years, along with detailed information on the motorcyclist, driver, roadway and environmental conditions, vehicle, collision type, and temporal characteristics. Specifically, motorcycles and vehicles are classified into three age groups: less than 6 years, between 6 and 11 years, and over 11 years. Since most vehicles colliding with motorcycles are passenger cars and trucks (over 90%), these are potential variables. In the UK, the weekend typically refers to Saturday and Sunday. Most workplaces

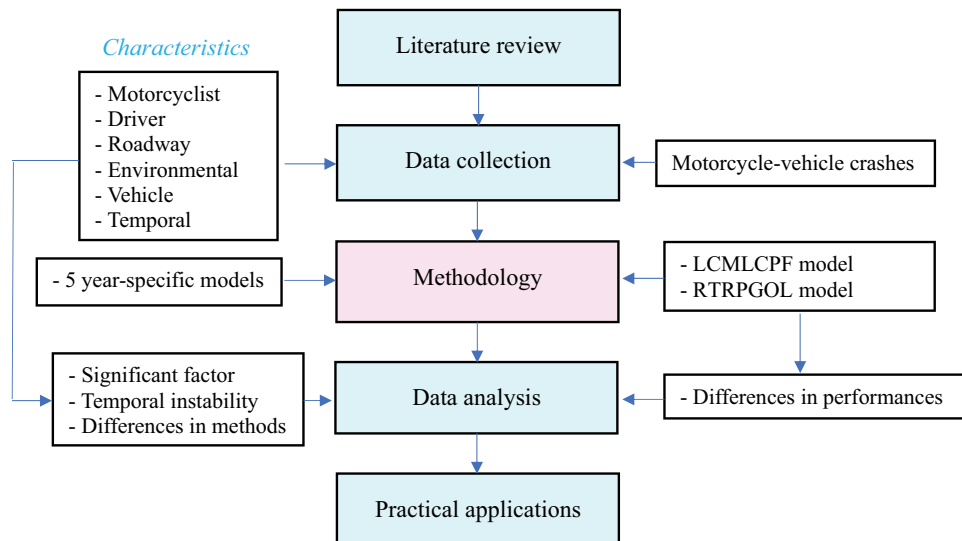
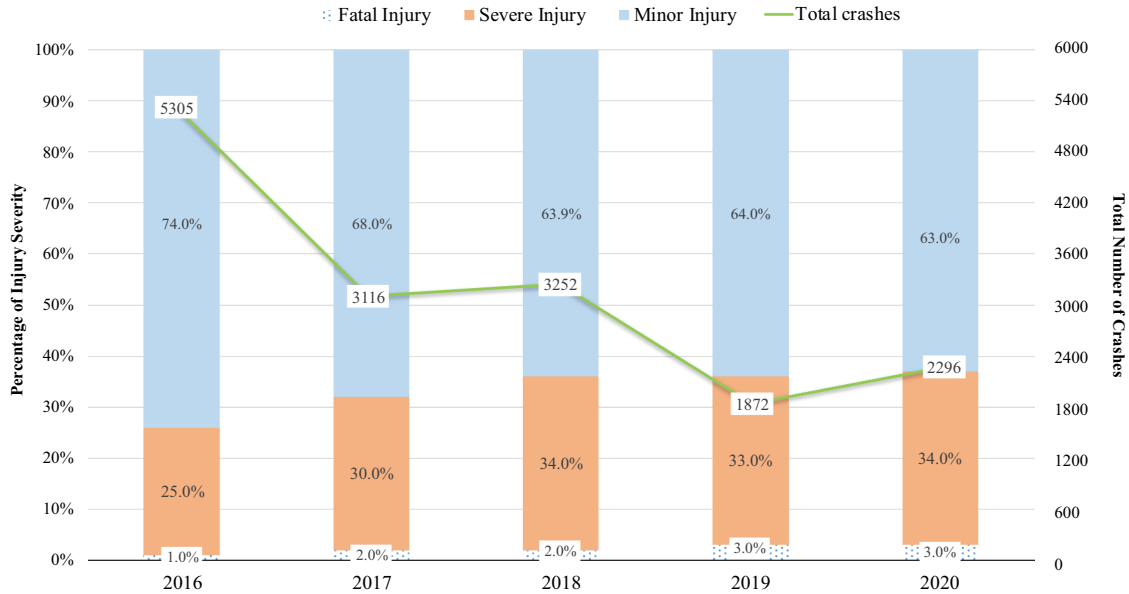


Figure 1. Outline of study activities.

Table 1. Motorcycle-vehicle crash observations from 2016 to 2020.

Year	2016	2017	2018	2019	2020
Fatal Injury	53	62	65	56	69
Severe Injury	1326	935	1106	618	781
Minor Injury	3926	2119	2081	1198	1446
Total	5305	3116	3252	1872	2296

**Figure 2.** Motorcycle-vehicle crash injury severity for 2016–2020 (UK).

and schools are closed on these two days, allowing people to engage in leisure, entertainment, and social activities.

Notably, the rate of older-age motorcyclists increased from 0.068 in 2016 to 0.116 in 2020, as shown in Table 2, indicating that more older motorcyclists are involved in collisions with other vehicles. Motorcycling has become more popular among older individuals in the UK as a hobby or mode of transportation. The increasing crash rate might be explained by the lack of targeted safety policies and enforcement for older motorcyclists, coupled with decreased vision, reaction time, and physical agility.

Previous research has demonstrated the importance of including crash type as an independent variable (Se et al. 2022; Wang et al. 2023; Yan et al. 2021). Including crash type as an independent variable helps capture these inherent differences and clarifies the factors influencing crash severity. Accounting for the crash type can improve the overall accuracy and explanatory power. Furthermore, understanding the role of crash type in influencing crash severity has significant policy and practical implications for improving motorcycle safety.

Methodology

Latent class multinomial logit with class probability functions model

The LCMLCP model allows the motorcyclists to collide with non-motorcycles to pertain to c distinct latent classes, while each class's possibility can be estimated by a specific multinomial logit model:

$$P_j(i|c) = \frac{e^{\beta_{ic} \cdot X_{ij}}}{\sum_{\forall I} e^{\beta_{ic} \cdot X_{ij}}} \quad (1)$$

where $P_j(i|c)$ denotes the possibility of injury outcome i in crash j and I denote the set of three possible motorcyclist-injury outcomes for crash j , and α_{ic} is a vector of estimable parameters corresponding to unobserved class c . The $P_j(i)$ specific to injury-level i of crash j can be specific as:

$$P_j(c) = \frac{e^{\alpha_{ic} \cdot Z_{ij}}}{\sum_{\forall C} e^{\alpha_{ic} \cdot Z_{ij}}} \quad (2)$$

where Z_{ij} denotes a vector of parameters affecting class c possibility for crash j and α_{ic} is the corresponding vector of the estimable parameters. By combining Eqs. (1) and (2), the unconditional possibility of motorcyclist crash j with injury outcome i can be expressed as

$$P_j(i) = \sum_{\forall C} P_j(c) \times P_j(i|c) \quad (3)$$

Likewise, the latent class models are based on the standard maximum likelihood methods (Greene and Hensher 2003). Additionally, the marginal effects are calculated and presented as average values across classes (Washington et al. 2020).

Generalized ordered logit model

In the traditional, ordered logit (OL) model, the discrete injury severity levels (y_i) are assumed to be associated with an underlying continuous latent variable (y_i^*). This latent variable is typically

Table 2. Descriptive statistics of the significant variables for motorcycle-vehicle crashes (2016–2020).

Variable	2016	2017	2018	2019	2020
	Count (Percentage)	Count (Percentage)	Count (Percentage)	Count (Percentage)	Count (Percentage)
Minor/severe/fatal injury	0.74/0.25/0.01	0.68/0.30/0.02	0.64/0.34/0.03	0.64/0.33/0.02	0.63/0.34/0.03
Motorcyclist characteristics					
Male MC indicator (1 if male, 0 otherwise)	2993 (93.4%)	2885 (92.6%)	3021 (92.9%)	1758 (93.9%)	2170 (94.5%)
Young-age MC indicator (1 if < 25, 0 otherwise) ^a	1295 (40.4%)	1274 (40.9%)	1184 (36.4%)	713 (38.1%)	794 (34.6%)
Middle-age MC indicator (1 if 25–55, 0 otherwise)	1651 (51.5%)	1524 (48.9%)	1655 (50.9%)	927 (49.5%)	1205 (52.5%)
Older-age MC indicator (1 if > 55, 0 otherwise)	218 (6.8%)	293 (9.4%)	380 (11.7%)	215 (11.5%)	266 (11.6%)
Urban motorcyclist indicator (1 if motorcyclist is from an urban area, 0 otherwise)	2497 (77.9%)	2147 (68.9%)	2455 (75.5%)	1355 (72.4%)	1724 (75.1%)
Driver characteristics					
Male driver indicator (1 if driver is male, 0 otherwise)	1997 (62.3%)	1851 (59.4%)	2000 (61.5%)	1136 (60.7%)	1384 (60.3%)
Young-age driver indicator (1 if < 25, 0 otherwise)	397 (12.4%)	371 (11.9%)	400 (12.3%)	236 (12.6%)	303 (13.2%)
Middle-age driver indicator (1 if 25–65, 0 otherwise)	1968 (61.4%)	2078 (66.7%)	2185 (67.2%)	1232 (65.8%)	1506 (65.6%)
Old-age driver indicator (1 if > 65, 0 otherwise)	215 (6.7%)	249 (8.0%)	280 (8.6%)	167 (8.9%)	177 (7.7%)
Roadway and environmental conditions					
Weather condition indicator (1 if fine, 0 otherwise)	2747 (85.7%)	2652 (85.1%)	2846 (87.5%)	1550 (82.8%)	1933 (84.2%)
Darkness with street light indicator (1 if darkness with street light, 0 otherwise)	695 (21.7%)	648 (20.8%)	615 (18.9%)	416 (22.2%)	498 (21.7%)
Darkness with street unlight indicator (1 if darkness with street unlight, 0 otherwise)	45 (1.4%)	62 (2.0%)	68 (2.1%)	26 (1.4%)	53 (2.3%)
Speed limit indicator (1 if speed limit is 20 mph, 0 otherwise)	170 (5.3%)	178 (5.7%)	198 (6.1%)	140 (7.5%)	181 (7.9%)
Speed limit indicator (1 if speed limit is 30 mph, 0 otherwise)	2202 (68.7%)	1935 (62.1%)	1880 (57.8%)	1136 (60.7%)	1318 (57.4%)
Speed limit indicator (1 if speed limit is 40 mph, 0 otherwise)	263 (8.2%)	308 (9.9%)	338 (10.4%)	150 (8.0%)	236 (10.3%)
Speed limit indicator (1 if speed limit is 50 mph, 0 otherwise)	125 (3.9%)	137 (4.4%)	140 (4.3%)	105 (5.6%)	108 (4.7%)
Speed limit indicator (1 if speed limit is 60 mph, 0 otherwise)	359 (11.2%)	442 (14.2%)	520 (16.0%)	292 (15.6%)	383 (16.7%)
Speed limit indicator (1 if speed limit is 70 mph, 0 otherwise)	87 (2.7%)	112 (3.6%)	172 (5.3%)	47 (2.5%)	67 (2.9%)
Roundabout indicator (1 if roundabout, 0 otherwise)	196 (6.1%)	240 (7.7%)	241 (7.4%)	122 (6.5%)	145 (6.3%)
Slip road indicator (1 if slip road, 0 otherwise)	22 (0.7%)	16 (0.5%)	23 (0.7%)	11 (0.6%)	30 (1.3%)
Single carriageway indicator (1 if road type is single carriageway, 0 otherwise)	2535 (79.1%)	2418 (77.6%)	2498 (76.8%)	1462 (78.1%)	1841 (80.2%)
Dual carriageway indicator (1 if road type is dual carriageway, 0 otherwise)	385 (12.0%)	365 (11.7%)	420 (12.9%)	240 (12.8%)	243 (10.6%)
Urban area indicator (1 if the crash occurred in an urban area, 0 otherwise)	2336 (72.9%)	2078 (66.7%)	2036 (62.6%)	1222 (65.3%)	1442 (62.8%)
Vehicle characteristics					
MC preceding collision (1 if straight, 0 otherwise)	1926 (60.1%)	1907 (61.2%)	2013 (61.9%)	1179 (63.0%)	1430 (62.3%)
Vehicle preceding collision (1 if straight, 0 otherwise)	968 (30.2%)	1038 (33.3%)	1174 (36.1%)	672 (35.9%)	866 (37.7%)
Young-age motorcycle (1 if < 6, 0 otherwise)	1423 (44.4%)	1418 (45.5%)	1463 (45.0%)	723 (38.6%)	1029 (44.8%)
Middle-age motorcycle (1 if 6–11, 0 otherwise)	660 (20.6%)	586 (18.8%)	572 (17.6%)	313 (16.7%)	402 (17.5%)
Older-age motorcycle (1 if >11, 0 otherwise)	689 (21.5%)	754 (24.2%)	872 (26.8%)	504 (26.9%)	581 (25.3%)
Young-age vehicle (1 if < 6, 0 otherwise)	1035 (32.3%)	1091 (35.0%)	1180 (36.3%)	638 (34.1%)	783 (34.1%)
Middle-age vehicle (1 if 6–11, 0 otherwise)	760 (23.7%)	732 (23.5%)	722 (22.2%)	406 (21.7%)	475 (20.7%)
Old-age vehicle (1 if > 11, 0 otherwise)	737 (23.0%)	720 (23.1%)	777 (23.9%)	404 (21.6%)	590 (25.7%)
Passenger car (1 if type of vehicle is passenger car; 0 otherwise)	2586 (80.7%)	2552 (81.9%)	2657 (81.7%)	1543 (82.4%)	1890 (82.3%)
Truck (1 if type of vehicle is truck; 0 otherwise)	340 (10.6%)	327 (10.5%)	354 (10.9%)	197 (10.5%)	266 (11.6%)
Type of collision					
Head-on (1 if head-on, 0 otherwise)	945 (29.5%)	953 (30.6%)	1057 (32.5%)	642 (34.3%)	744 (32.4%)
Sideswipe (1 if sideswipe, 0 otherwise)	1369 (42.7%)	1212 (38.9%)	1246 (38.3%)	695 (37.1%)	861 (37.5%)
Rear-end (1 if rear-end, 0 otherwise)	612 (19.1%)	661 (21.2%)	689 (21.2%)	397 (21.2%)	496 (21.6%)
Temporal variables					
Time indicator (1 if morning peak hours, 0 otherwise)	506 (15.8%)	471 (15.1%)	537 (16.5%)	258 (13.8%)	257 (11.2%)
Time indicator (1 if evening off-peak hours, 0 otherwise)	151 (4.7%)	131 (4.2%)	133 (4.1%)	97 (5.2%)	96 (4.2%)
Day of the week indicator (1 if Monday, 0 otherwise)	404 (12.6%)	402 (12.9%)	380 (11.7%)	262 (14.0%)	285 (12.4%)
Day of the week indicator (1 if Tuesday, 0 otherwise)	445 (13.9%)	377 (12.1%)	455 (14.0%)	230 (12.3%)	292 (12.7%)
Day of the week indicator (1 if Wednesday, 0 otherwise)	478 (14.9%)	483 (15.5%)	446 (13.7%)	266 (14.2%)	333 (14.5%)
Day of the week indicator (1 if Thursday, 0 otherwise)	487 (15.2%)	455 (14.6%)	468 (14.4%)	311 (16.6%)	333 (14.5%)
Day of the week indicator (1 if Friday, 0 otherwise)	503 (15.7%)	499 (16.0%)	514 (15.8%)	279 (14.9%)	363 (15.8%)
Day of the week indicator (1 if Saturday, 0 otherwise)	529 (16.5%)	502 (16.1%)	572 (17.6%)	273 (14.6%)	374 (16.3%)
Day of the week indicator (1 if Sunday, 0 otherwise)	359 (11.2%)	399 (12.8%)	416 (12.8%)	251 (13.4%)	317 (13.8%)
Weekend indicator (1 if Weekend, 0 otherwise)	888 (27.7%)	901 (28.9%)	989 (30.4%)	524 (28.0%)	691 (30.1%)
Season indicator (1 if summer, 0 otherwise)	881 (27.5%)	857 (27.5%)	904 (27.8%)	457 (24.4%)	652 (28.4%)

^aAges are in years. MC = motorcyclist.

specified by the following linear function (Bhowmik, Yasmin, and Eluru 2019; Eluru et al. 2013; Washington et al. 2020):

$$y_i^* = \mathbf{X}_i \boldsymbol{\beta} + \varepsilon_i, y_i = j, \text{ if } \mu_{j-1} < y_i^* < \mu_j, \text{ for } i = 1, 2, \dots, N; j = 1, 2, \dots, J \quad (4)$$

where i ($i = 1, 2, \dots, N$) represents the drivers, \mathbf{X}_i is a vector of exogenous variables (excluding a constant), μ represents the thresholds associated with these severity levels, $\boldsymbol{\beta}$ is a vector of unknown

parameters to be estimated, j are the integer ordered injury-severity levels, ε is the random disturbance term assumed to be standard logistic.

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

$$\mu_{i,j} = \mu_{i,j-1} + e^{(t_j+d_jS_i)} \quad (5)$$

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

Random thresholds-parameters generalized ordered logit model

The random thresholds-parameters generalized ordered logit (RTRPGOL) model extends the GOL model, allowing for unobserved heterogeneity in the parameters and the thresholds. First, to allow the thresholds to vary across the observations concurrently, Eq. (5) can be re-written as (Fountas and Anastasopoulos 2017):

$$\mu_{i,j} = \mu_{i,j-1} + e^{(t_j+\gamma_j\mu_{ij}+d_jS_i)} \quad (6)$$

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

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

$$\beta_i = \beta + \Gamma w_i \quad (7)$$

where β is the mean of the random parameters' vectors, Γ is the diagonal matrix of SDs, and w_i is a normally distributed term with mean zero and variance one. A simulated maximum likelihood estimation process is used to improve the estimation efficiency. The process involves a Halton sequence approach that draws the random values of β from the parameter density function $q(\beta|\varphi)$, where φ denotes a vector of the parameters of the density distribution (e.g. mean and SD, in the case of the normal distribution).

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

$$P(y = j) = \Phi(\mu_j - \beta_i X_i) - \Phi(\mu_{j+1} - \beta_i X_i) \quad (8)$$

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

Temporal instability (transferability) test

Two series of likelihood ratio tests are estimated to investigate the temporal instability in the effects of factors determining the injury outcomes of motorcycle crashes. Firstly, one series of likelihood ratio tests is implemented to estimate the temporal stability between the joint temporal model and each separate model (Wang et al. 2023):

$$\chi_{t_1}^2 = -2 \left[LL(\beta_{2016-2020}) - \sum_{2016}^{2020} LL(\beta_t) \right] \quad (9)$$

where $LL(\beta_{2017-2019})$ represents the convergence model's log-likelihood of motorcycle crashes for five years (2016–2020), while $LL(\beta_t)$ denotes the individual convergence model's log-likelihood using only one year t (2016, 2017, 2018, 2019, and 2020) data. Then, the χ^2 test gives a value of 395.66 with 128 degrees of freedom,¹

specifying that the null hypothesis that these models stay temporal stable can be rejected with >99.99% confidence.

Then, another series of likelihood ratio tests are proposed to compare the models concerning two individual years and examine whether the estimated parameter is transferable across these years (Alnawmasi and Mannering 2019):

$$\chi_{t_2}^2 = -2 \left[LL(\beta_{y_1 y_2}) - LL(\beta_{y_1}) \right] \quad (10)$$

where $LL(\beta_{y_1 y_2})$ denotes the log-likelihood at the convergence of the model estimating parameters from y_2 while using data from subgroup y_1 , and $LL(\beta_{y_1})$ denotes the log-likelihood at the convergence of the model using the data subgroup y_1 .

Other than likelihood ratio tests, the out-of-sample prediction could also be used, where one model's estimated parameters could be used to predict the data from another subgroup (Alnawmasi and Mannering, 2022; Wang, Chen, Zhang, and Cheng 2022). Specifically, the predictions of out-of-sample using the LCMLCP model will be estimated by averaging the differences in possibilities (Alnawmasi and Mannering, 2022):

$$P(i) = \frac{1}{N} \sum_{n=1}^N \frac{\exp(\beta_{ic} X_{ij} + \alpha_{ic} Z_{ij})}{\sum_{c=1}^C \sum_{i=1}^I \exp(\beta_{ic} X_{ij} + \alpha_{ic} Z_{ij})} \quad (11)$$

where the notations and symbols are denoted in Equations (1)–(3).

Then, the out-of-sample predictions based on the RTRPGOL model can also be calculated as:

$$P(i) = \frac{1}{N} \sum_{n=1}^N \frac{\Phi(\mu_j - \beta_i X_i) - \Phi(\mu_{j+1} - \beta_i X_i)}{\sum_{i=1}^I \sum_{j=1}^J \Phi(\mu_j - \beta_i X_i) - \Phi(\mu_{j+1} - \beta_i X_i)} \quad (12)$$

where the notations and symbols are denoted in Equations (7)–(9).

Results

Temporal stability analysis

Table 2 shows whether the null hypothesis that the parameters that remain stable during the two-year period can be rejected based on the LCMLCP model. Likewise, Table 3 indicates the same results based on the RTRPGOL model. Finally, all the two-year models stay unstable, showing that the null hypothesis can be rejected under >99% confidence level, indicating that the estimated parameters vary across the five years.

Table 4 shows the means of the differences in probabilities using the specific year model's parameters to predict the following year's observations based on the LCMLCP model. For instance, using the

Table 3. The likelihood ratio test results of motorcycle-vehicle crash models based on the LCMLCP models between different periods (degrees of freedom in parentheses and confidence level in brackets).

y_1	y_2				
	2016	2017	2018	2019	2020
2016	–	84.87(32) [99.99%]	135.20(42) [99.99%]	43.26(31) [99.99%]	113.23(26) [99.99%]
2017	56.64(34) [99.99%]	–	88.80(42) [99.99%]	62.26(31) [99.99%]	26.57(26) [99.11%]
2018	84.91(34) [99.99%]	86.26(32) [99.99%]	–	58.44(31) [99.99%]	76.57(26) [99.99%]
2019	42.56(34) [99.99%]	91.05(32) [99.99%]	124.75(42) [99.99%]	–	66.23(26) [99.99%]
2020	47.01(34) [99.99%]	46.78(32) [99.99%]	87.61(42) [99.99%]	54.33(31) [99.99%]	–

Table 4. Results of the likelihood ratio test of motorcycle-vehicle crash models based on the RTRPGOL models between different periods (degrees of freedom in parentheses and confidence level in brackets).

y_1	y_2				
	2016	2017	2018	2019	2020
2016	–	73.72(20) [99.99%]	83.26(43) [99.98%]	63.26(31) [99.95%]	89.05(14) [99.99%]
2017	72.80 (43) [99.99%]	–	95.37(43) [99.99%]	83.81(31) [99.99%]	61.09(14) [99.99%]
2018	76.45(43) [99.87%]	95.57(20) [99.99%]	–	92.80(31) [99.99%]	86.51(14) [99.99%]
2019	93.68(43) [99.99%]	64.72(20) [99.99%]	105.83(43) [99.99%]	–	79.24(14) [99.99%]
2020	89.07(43) [99.99%]	51.09(20) [99.98%]	86.51(43) [99.99%]	79.24(31) [99.99%]	–

2016 model parameters to predict the 2017 data can overestimate the severe injury prediction by 0.0661, while underestimating the minor and fatal injury prediction by 0.0606 and 0.0055, respectively. Based on RTRPGOL models, most out-of-sample prediction results shown in Table 5 are higher than those of LCMLCP models. For instance, adopting the 2016 model parameters to predict 2017 data can overestimate the severe injury prediction by 0.1184 in RTRPGOL models. Given this, the considerable differences through out-of-sample prediction shown in Tables 5 and 6 also confirm the temporal variations.

Moreover, analyzing data on a yearly basis using separate models can reveal significant temporal instability due to changes in human behavior, vehicle characteristics, traffic patterns, and economic conditions. This study investigates temporal instability using a crash dataset spanning five years, which constitutes a key contribution to the existing research. Additionally, the 2021 dataset can be utilized for prediction based on the estimated parameters from prior years (2016–2020) in this study.

Comparison of models

This section compares the performance of the two models before discussing the estimation results. This study estimates two different models by evaluating alternative outcome frameworks for modeling crash injury severity: the LCMLCP and RTRPGOL models.⁴ Hence, the entire comparison focuses on these two models. The estimation results based on LCMLCP and RTRPGOL models are presented in Tables 7–8, respectively. LCMLCP models with two, three, and four classes are estimated for each year, and the AIC and BIC values are

computed to determine the optimal number of latent classes. For the year 2016, the AIC values for the two-, three-, and four-class models are 6249.610/6473.208 (34 parameters), 6384.858/6689.102 (49 parameters), and 6418.386/6911.616 (75 parameters), respectively. Since a similar phenomenon is observed in the models for the years 2017 to 2020, the two-class models are selected. The class-specific probabilities are represented as a set of fixed constants (see Eq. (2)), as segmenting based on crash-specific characteristics did not yield a model with superior data fit. The distribution of crash severity outcomes within each class from 2017 to 2020 is presented in Table 7. The results indicate that Class 1 exhibits a higher proportion of fatal and severe injuries, as well as a greater class probability compared to Class 2 across all years, except for 2020.

Notably, even if a parameter has a low t-stat, it may still be retained in the model if it is deemed theoretically important or supported by prior knowledge. In such cases, the effects of these parameters are analyzed, even if they do not achieve statistical significance at a 95% confidence level. For instance, the 'MI] Young-age MC indicator (1 if <25, 0 otherwise)' is significant for the years 2018 and 2020, indicating an inconsistent trend in the results. It increases the likelihood of minor injury for both classes in the 2018 model, while it decreases for class 1 and increases for class 2 in the 2020 model. In the 2016 model, the results are opposite to those in the 2020 model, suggesting potential temporal instability.

As shown in Table 9, the log-likelihood values at convergence for the various frameworks are as follows: (1) for the 2016 model, RTRPGOL (with 43 parameters) is -3077.717 and LCMLCP (with 34 parameters) is -3090.805 , (2) for the 2017 model, RTRPGOL (with 20 parameters) is -2054.615 and LCMLCP (with 32 parameters) is -2028.373 ; (3) for the 2018 model, RTRPGOL (with 43 parameters) is -2226.146 and LCMLCP (with 42 parameters) is -2243.256 ; (4) for the 2019 model, RTRPGOL (with 31 parameters) is -1270.277 and LCMLCP (with 31 parameters) is -1266.06 ; and (5) for the 2020 model, RTRPGOL (with 14 parameters) is -1607.764 and LCMLCP (with 26 parameters) is -1582.151 . After comparing the ordered and unordered frameworks, the LCMLCP model is found to slightly outperform the RTRPGOL model in terms of the goodness-of-fit measures (except for 2016 and 2018), indicating that the factors have uncertainty and variability by time from the side. Nonetheless, it is noted that the LCMLCP model provides a higher ρ^2 than the RTRPGOL model in all years. The estimation results obtained good ρ^2 values of over 0.370, but less than 0.100 for all the RTRPGOL models. Moreover, there is a great deal variation in the AIC and BIC values between the two models. For instance, the AIC value of the LCMLCP is higher than that of

Table 5. Difference in probabilities by temporal instability for multi-vehicle motorcycle crashes based on LCMLCP models.

Predict year Base year	2017			2018			2019			2020		
	MI	SI	FI	MI	SI	FI	MI	SI	FI	MI	SI	FI
2016	-0.0606	0.0661	-0.0055	0.0064	-0.0106	0.0042	0.0209	-0.0188	0.0021	0.0114	-0.0146	0.0032
2017	–	–	–	0.0036	-0.0048	0.0084	0.0484	-0.0472	-0.0012	0.0238	-0.0169	-0.0069
2018	–	–	–	–	–	–	0.0638	-0.0541	-0.0097	0.0306	-0.0283	-0.0023
2019	–	–	–	–	–	–	–	–	–	0.0337	-0.0359	0.0022

Table 6. Difference in probabilities by temporal instability for multi-vehicle motorcycle crashes based on RTRPGOL models.

Predict year Base year	2017			2018			2019			2020		
	MI	SI	FI	MI	SI	FI	MI	SI	FI	MI	SI	FI
2016	-0.0011	0.1184	-0.1173	0.0124	-0.0136	0.0012	0.0003	-0.0002	-0.0001	-0.0015	0.1071	-0.1056
2017	–	–	–	0.0014	-0.1482	0.1468	0.0008	-0.1349	0.1341	0.0004	-0.0418	0.0414
2018	–	–	–	–	–	–	-0.0001	0.0002	-0.0001	-0.0021	0.1075	-0.1054
2019	–	–	–	–	–	–	–	–	–	-0.0019	0.1072	-0.1053

Table 7. Results of the LCMLCP model for motorcycle-vehicle crashes for 2016–2020 (*t*-stat. in parentheses).

Variable (LCMLCP)	2016		2017		2018		2019		2020	
	Latent Class 1	Latent Class 2	Latent Class 1	Latent Class 2	Latent Class 1	Latent Class 2	Latent Class 1	Latent Class 2	Latent Class 1	Latent Class 2
[M] Constant	2.793 (2.57)	-1.166 (-0.04)	14.441 (1.85)	1.193 (0.63)	5.254 (4.82)	4.349 (4.10)	6.030 (4.15)	2.254 (1.18)	4.793 (3.57)	5.136 (0.12)
[S] Constant	2.623 (0.58)	2.827 (5.50)	0.222 (0.33)	1.165 (2.02)	3.916 (3.70)	0.458 (0.35)	5.284 (3.83)	0.931 (0.90)	2.194 (4.54)	50.785 (0.10)
Motorcyclist characteristics										
[M] Male MC indicator (1 if male, 0 otherwise)	-	-	-1.035 (-0.99)	-0.632 (-1.76)	-0.384 (-1.34)	-1.889 (-2.18)	-	-	1.690 (2.53)	-0.122 (-0.24)
[M] Young-age MC indicator (1 if < 25, 0 otherwise)	3.554 (0.23)	-1.430 (-1.46)	-	-	0.516 (2.05)	1.195 (2.42)	-	-	-0.576 (-1.04)	1.408 (4.11)
[F] Young-age MC indicator (1 if < 25, 0 otherwise)	-	-	-2.442 (-2.20)	6.834 (0.61)	-	-	-	-	-	-
[M] Middle-age MC indicator (1 if 25–55, 0 otherwise)	-	-	-	-	0.621 (2.45)	0.231 (0.51)	-	-	-	-
[S] Middle-age MC indicator (1 if 25–55, 0 otherwise)	0.739 (3.04)	1.479 (4.05)	-	-	-	-	-	-	-	-
[M] Urban MC indicator (1 if motorcyclist is from an urban area, 0 otherwise)	0.369 (1.53)	0.789 (1.56)	-	-	-	-	-	-	-	-
Driver characteristics										
[M] Male driver indicator (1 if male, 0 otherwise)	-	-	-0.204 (-0.55)	-0.394 (-1.67)	-	-	-	-	-	-
[M] Young-age driver indicator (1 if <25, 0 otherwise)	-	-	-	-	-	-	2.666 (4.36)	-4.544 (-0.61)	-	-
Roadway and environmental conditions										
[M] Weather condition indicator (1 if fine, 0 otherwise)	-	-	-10.867 (0.55)	-0.649 (-2.36)	0.577 (1.86)	-0.589 (-0.54)	-1.634 (-3.87)	2.315 (0.04)	-	-
[F] Darkness with street light indicator (1 if darkness with street light, 0 otherwise)	-	-	1.271 (1.67)	1.916 (1.03)	-	-	-	-	-	-
[M] Speed limit indicator (1 if 30 mph, 0 otherwise)	0.726 (3.30)	-1.031 (-2.14)	-	-	-	-	-	-	-2.580 (-1.93)	1.488 (3.57)
[F] Speed limit indicator (1 if 30 mph, 0 otherwise)	-	-	-0.861 (-1.80)	-0.468 (-0.14)	-24.584 (-0.22)	-0.534 (-1.57)	-	-	-	-
[M] Speed limit indicator (1 if 60 mph, 0 otherwise)	-	-	-	-	-	-	-0.752 (-2.37)	-3.593 (-0.10)	-	-
[S] Speed limit indicator (1 if 60 mph, 0 otherwise)	-	-	-	-	-	-	-	-	33.013 (0.45)	-1.478 (-3.37)
[S] SC indicator (1 if SC, 0 otherwise)	-	-	-	-	-	-	-	-	-1.705 (-1.47)	1.407 (2.85)
[F] SC indicator (1 if SC, 0 otherwise)	-	-	-	-	-	-	-	-	-2.973 (-2.36)	4.869 (0.12)
[M] DC indicator (1 if DC, 0 otherwise)	-	-	-	-	-0.627 (-2.84)	-0.765 (-1.53)	-	-	-	-
[M] Urban area indicator (1 if the crash occurred in an urban area, 0 otherwise)	-1.799 (-3.04)	17.300 (0.06)	1.785 (3.48)	1.418 (1.98)	0.218 (0.86)	1.498 (3.54)	3.267 (5.18)	-6.517 (-0.26)	-0.837 (-1.16)	2.070 (4.96)
Vehicle characteristics										
[M] MC preceding collision (1 if straight, 0 otherwise)	-	-	-0.950 (-2.08)	-0.125 (-0.62)	-	-	-	-	-1.750 (-2.44)	0.101 (0.39)
[F] MC preceding collision (1 if straight, 0 otherwise)	-	-	-	-	0.288 (0.23)	0.795 (2.36)	-	-	-	-
[M] Vehicle preceding collision (1 if straight, 0 otherwise)	-	-	-0.308 (-0.86)	-0.805 (-2.06)	-0.323 (-1.92)	-1.076 (-2.77)	-	-	-	-
[S] Vehicle preceding collision (1 if straight, 0 otherwise)	-	-	-	-	-	-	0.920 (2.86)	-76.783 (0.00)	-	-
[F] Vehicle preceding collision (1 if straight, 0 otherwise)	-	-	-	-	-	-	2.164 (3.60)	-77.906 (-0.03)	-58.980 (-0.13)	1.945 (4.02)
[M] Young-age motorcycle (1 if <6, 0 otherwise)	-	-	-	-	-	-	-	-	1.690 (2.53)	-0.262 (-0.95)
[S] Young-age motorcycle (1 if <6, 0 otherwise)	-	-	-	-	-0.804 (-3.47)	0.804 (0.87)	-1.163 (-4.03)	1.396 (1.50)	-	-
[F] Young-age motorcycle (1 if <6, 0 otherwise)	-	-	0.771 (2.05)	-0.984 (-0.33)	-	-	-	-	-	-
[M] Middle-age motorcycle (1 if 6–11, 0 otherwise)	0.237 (0.70)	-1.125 (-2.35)	-	-	-	-	-	-	-	-
[S] Middle-age motorcycle (1 if 6–11, 0 otherwise)	-	-	-	-	-0.590 (-2.39)	-2.012 (-1.85)	-0.668 (-1.52)	90.175 (0.92)	-	-
[S] Old-age vehicle (1 if >11, 0 otherwise)	0.449 (2.69)	0.018 (0.07)	-	-	-	-	-	-	-	-
[M] Passenger car (1 if passenger car, 0 otherwise)	-	-	1.177 (2.91)	-0.224 (-0.07)	-	-	-	-	-	-
[F] Passenger car (1 if passenger car, 0 otherwise)	-	-	-	-	-	-	-0.408 (-0.72)	-1.619 (-2.11)	-	-

(Continued)

Table 7. (Continued).

Variable (LCMLCP)	2016		2017		2018		2019		2020	
	Latent Class 1	Latent Class 2	Latent Class 1	Latent Class 2	Latent Class 1	Latent Class 2	Latent Class 1	Latent Class 2	Latent Class 1	Latent Class 2
[MI] Truck (1 if truck, 0 otherwise)	-	-	-	-	-0.395 (-1.56)	-1.035 (-1.99)	-	-	-	-
Collision Type										
[MI] Head-on (1 if head-on, 0 otherwise)	-0.586 (-0.53)	-1.349 (-2.33)	-0.991 (-2.56)	-2.065 (-0.60)	-0.666 (-2.83)	-0.074 (-0.19)	-	-	-	-
[FI] Head-on (1 if head-on, 0 otherwise)	-1.258 (-1.17)	-1.363 (-4.36)	-	-	-	-	-	-	-	-
[SI] Sideswipe (1 if sideswipe, 0 otherwise)	-	-	-	-	-3.069 (-1.14)	6.046 (4.12)	-	-	-	-
[MI] Rear-end (1 if rear-end, 0 otherwise)	0.340 (1.72)	0.014 (0.03)	-	-	-	-	-	-	-	-
[SI] Rear-end (1 if rear-end; 0 otherwise)	-	-	-	-	0.567 (1.97)	0.994 (1.27)	-	-	-	-
Temporal variables										
[MI] Time indicator (1 if morning peak hours, 0 otherwise)	-	-	-	-	-	-	0.460 (1.59)	67.82 (0.01)	-	-
[MI] Weekday indicator (1 if Monday, 0 otherwise)	-	-	-	-	-0.002 (-0.01)	1.389 (1.92)	-	-	-	-
[FI] Weekday indicator (1 if Monday, 0 otherwise)	-	-	-	-	-	-	0.898 (1.94)	-19.400 (-0.17)	-	-
[MI] Weekday indicator (1 if Tuesday, 0 otherwise)	0.418 (1.71)	0.178 (0.40)	-	-	-	-	-	-	-	-
[MI] Weekday indicator (1 if Wednesday, 0 otherwise)	-	-	-	-	-	-	-1.065 (2.50)	-12.854 (-0.02)	-	-
[SI] Weekday indicator (1 if Saturday, 0 otherwise)	-0.409 (-1.82)	-0.85 (-1.87)	-	-	-	-	-	-	-	-
[FI] Weekday indicator (1 if Saturday, 0 otherwise)	-1.200 (-0.57)	-2.070 (-2.58)	-	-	-	-	-	-	-	-
[MI] Season indicator (1 if summer, 0 otherwise)	-	-	-	-	-0.422 (-2.40)	0.838 (2.21)	-	-	-	-
Latent class probability variables (defined for latent Class 1)										
Constant	0.607 (3.24)	-	0.649 (1.87)	-	1.155 (3.64)	-	1.109 (10.28)	-	-	-
Weekend indicator (1 if Weekend, 0 otherwise)	-	-	-0.278 (-2.35)	-	-	-	-	-	-0.244 (-1.72)	-
Roundabout indicator (1 if roundabout, 0 otherwise)	0.476 (2.11)	-	0.528 (2.14)	-	-	-	-	-	-0.788 (-2.51)	-
SC indicator (1 if SC, 0 otherwise)	-	-	-	-	-0.701 (-3.19)	-	-	-	-	-
Slip road indicator (1 if slip road, 0 otherwise)	-	-	-	-	-	-	-1.241 (-1.94)	-	-	-
Weather condition indicator (1 if fine, 0 otherwise)	-0.355 (-2.17)	-	-	-	-0.488 (-1.81)	-	-	-	-	-
Speed limit indicator (1 if 30 mph, 0 otherwise)	0.524 (3.99)	-	-	-	-	-	-	-	-	-
Speed limit indicator (1 if 60 mph, 0 otherwise)	-	-	-	-	-0.409 (-2.06)	-	-	-	-	-
DC indicator (1 if DC, 0 otherwise)	-	-	-0.349 (-2.25)	-	-	-	-	-	-	-
Weekday indicator (1 if Tuesday, 0 otherwise)	-	-	-	-	-	-	-0.394 (-2.16)	-	-	-
Components										
Crash population share	0.663	0.337	0.582	0.418	0.636	0.364	0.740	0.260	0.338	0.662
Crash injury severity										
Fatal Injury	0.011	0.009	0.022	0.018	0.021	0.018	0.032	0.024	0.027	0.031
Severe Injury	0.258	0.234	0.313	0.282	0.354	0.316	0.347	0.281	0.313	0.354
Minor Injury	0.731	0.757	0.666	0.700	0.625	0.665	0.620	0.695	0.659	0.615
Number of parameters (K)	34		32		42		31		26	
Number of observations (N)	5305		3116		3252		1872		2296	
Log-likelihood at zero	-5828.138		-3423.276		-3572.687		-2056.602		-2522.414	
Log-likelihood at convergence	-3090.805		-2028.373		-2243.256		-1266.06		-1582.151	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.470		0.407		0.372		0.384		0.373	
Akaike information criterion (AIC)	6249.610		4120.746		4570.512		2594.120		3216.302	
Bayesian information criterion (BIC)	6473.208		4314.164		4826.167		2765.698		3365.514	

^aMC = motorcyclist, SC = single carriageway, and DC = dual carriageway. Ages are in years.

^bA dash means that the corresponding variable is not significant.

the RTRPGOL model (6249.610 versus 6241.434), while the BIC value of the LCMLCP model was less (6473.208 versus 6524.219). Similarly, the comparisons between the two models also indicate the variations across the five years.

It should be noted that variance inflation factor (VIF) analysis is estimated based on the estimation from two models (O'Brien 2007). The VIF values for all significant variables are below 5, indicating no significant multicollinearity in either model.

To show the differences in determinants in the two heterogeneity methodological approaches, Table 10 summarizes the determinants with the corresponding impact trend. Several variables are significant in both of the two approaches, while several variables, such as the old-age MC indicator (1 if >55, 0 otherwise), old-age driver indicator (1 if >65, 0 otherwise), and time indicator (1 if evening off-peak hour, 0 otherwise) are only significant in RTRPGOL models. Moreover, the young-age MC indicator (1 if <25 years, 0 otherwise) is not significant in the 2017 LCMLCP model but significant in the RTRPGOL model. The season indicator (1 if summer, 0 otherwise) is only significant in the 2018 LCMLCP model, while it is significant in all the 5 years except in 2019. Such differences could result from variations in capturing unobserved heterogeneities among the different frameworks in the two models. A similar phenomenon could also be seen in the research of Wang et al. (2023).

Other than the differences in the determinants of the two models, potential differences also exist in the marginal effects of the same contributing factors in the two models. Tables 11 and 12 show the marginal effects of the determinants based on the LCMLCP and RTRPGOL models, respectively. Figure 3 indicates the example of the urban area indicator (1 if the crash occurred in an urban area, 0 otherwise). There is slight variation in the effect degree of this variable in the five years except for 2020⁵. The RTRPGOL model tends to have more variability in marginal effects over time than the LCMLCP model, with one sample of the head-on type indicator shown in Figure 4. Otherwise, the marginal effects across the five years reveal the temporal effects of the determinants. A similar phenomenon can also be found in the effects of other variables.

Recent empirical evidence from many studies suggests that the superiority of one model over another can be data-dependent (Eluru, Bhat, and Hensher 2008; Yasmin and Eluru 2013). Given this, the LCMLCP model with a higher ρ^2 values is leveraged to quantitatively describe the impact of explanatory variables on driver injury-severity in terms of motorcyclist, driver, roadway and environmental, vehicle, collision type, and temporal-specific characteristics and explore how these factors change over the years. Thus, the following discussion regarding the significance of determinants would be conducted based on the results based on LCMLCP models.

Significance of determinants

Motorcyclist characteristics

The male indicator is observed to be statistically significant, specific to minor injury in the 2017, 2018, and 2020 models. The marginal effects in Table 11 indicate the temporal stability of the male indicators, showing higher risk levels (increased severe/fatal injury likelihood and decreased minor injury likelihood). This finding supports recent evidence (Pai and Saleh 2008; Se et al. 2022), stating that male motorcyclists are more likely to take aggressive riding behaviors than their counterparts.

Regarding age, the younger motorcyclist indicator (younger than 25 years old) is significant in all the models except for 2019. The marginal effects specify that the probabilities of severe injuries consistently decreased in 2016, 2017, 2018, and 2020, while

potential temporal instability exists in the effects on minor/fatal injuries. Similar variations also exist in the influences on minor/severe injuries of middle-aged motorcyclist indicators, whereas middle-aged motorcyclists tend to decrease the fatal injury possibilities for 2016 and 2018. Possible differences in the effects of younger and middle-aged motorcyclists might be attributed to the changes in body capability and reaction behaviors (Schneider and Savolainen 2011). These temporal instability findings might be explained by the differences in the physiological conditions, riding skills, environment, and other potential elements (Mannering 2018).

Notably, urban motorcyclists are related to fewer injury outcomes, with decreased severe/fatal injury likelihood and increased minor injury likelihood. Urban motorcyclists tend to obey traffic regulations along with the separate motorcycle lanes in urban areas.

In the UK, there is a well-developed cycling infrastructure, including segregated cycle tracks, bicycle rental systems, and bicycle parking facilities in urban areas within cities like London, Manchester, Birmingham, and Bristol. Due to the relatively low frequency of dedicated motorcycle lanes, The UK government and local authorities have been promoting the development of cycling infrastructure to enhance traffic safety, reduce carbon emissions, and improve public health (Vardoulakis et al. 2018).

Driver characteristics

Regarding the drivers of other vehicles colliding with motorcycles, only male and younger driver indicators are statistically significant in one specific model. The male drivers tend to increase the severe/fatal injury likelihood by 0.0304/0.0029 in the 2017 model. The male drivers' more frequent speeding or aggressive driving might be a possible explanation (Yan et al. 2021). For the 2019 model, the younger drivers increase the possibility of severe/fatal injuries by 0.0951/0.0048, indicating greater threats of younger drivers on motorcycle safety. This potential reason might be the fewer experiences and worse driving skills corresponding to this age group of drivers younger than 25 years (Jung, Xiao, and Yoon 2013).

Roadway and environmental characteristics

As for weather conditions, fine weather is positively associated with fatal injury likelihood for 2016–2018. Under perfect visibility in fine weather conditions, the motorcyclists might be casual or distracted, taking higher speeding. The darkness conditions increase the fatal injury likelihood by 0.0019 in the 2017 model.

Showing possible temporal instability, the marginal effects of 30 mph and 60 mph speed limit specific to fatal injury state that the higher speed limit is positively related to higher injury outcomes (Chang et al. 2021; Pai and Saleh 2008). The single carriageway indicator increases the fatal injury probability in 2020, while the dual carriageway increases the severe/fatal injury likelihood in 2018. Consistently, the urban area tends to decrease the injury levels for all year periods. Similar to existing studies (Shaheed et al. 2013), urban areas are also found to reduce the likelihood of severe injury.

Vehicle characteristics

The variable reflecting the straight movement of motorcycles preceding collision is statistically significant for 2017, 2018, and 2020. This variable has a higher risk of fatal injuries, which might be due to the high differences in speed between motorcycles and other vehicles, causing severe outcomes in head-on or rear-end crashes (Se et al. 2022).

For motorcycle age, motorcycles less than 6 years old are found to decrease the risk levels (decreased probabilities of severe/fatal

Table 8. Results of parameter estimation of the RTRPGOL model for motorcycle-vehicle crashes for 2016–2020.³

Variable (RTRPGOL)	2016		2017		2018		2019		2020	
	Param.	t-stat.	Param.	t-stat.	Param.	t-stat.	Param.	t-stat.	Param.	t-stat.
Constant	-1.426	-2.75	-1.372	-5.63	-4.583	-4.35	-1.908	-3.14	-1.196	-4.66
<i>SD of parameter density function</i>	2.911	3.31	–	–	–	–	–	–	–	–
Motorcyclist characteristics										
Male MC indicator (1 if male, 0 otherwise)	–	–	0.418	2.52	2.268	3.57	–	–	0.531	2.42
<i>SD of parameter density function</i>	–	–	–	–	1.523	3.02	–	–	–	–
Young-age MC indicator (1 if <25, 0 otherwise)	-1.845	-2.69	–	–	-1.943	-3.42	–	–	-0.266	-2.72
<i>SD of parameter density function</i>	5.878	3.26	–	–	–	–	–	–	–	–
Middle-age MC indicator (1 if 25–55, 0 otherwise)	–	–	–	–	-1.590	-3.25	–	–	–	–
<i>SD of parameter density function</i>	–	–	–	–	4.185	3.68	–	–	–	–
Urban MC indicator (1 if motorcyclist is from an urban area, 0 otherwise)	-0.686	-2.78	–	–	–	–	–	–	–	–
Driver characteristics										
Male driver indicator (1 if male, 0 otherwise)	–	–	0.210	2.51	–	–	–	–	–	–
Old-age driver indicator (1 if >65, 0 otherwise)	1.175	2.45	–	–	–	–	–	–	–	–
<i>SD of parameter density function</i>	3.454	2.91	–	–	–	–	–	–	–	–
Roadway and environmental conditions										
Weather condition indicator (1 if fine, 0 otherwise)	–	–	0.470	3.83	1.093	2.69	–	–	–	–
Speed limit indicator (1 if 30 mph, 0 otherwise)	-1.394	-3.72	-0.365	-3.72	-2.448	-3.60	–	–	–	–
<i>SD of parameter density function</i>	1.209	3.86	–	–	3.877	4.03	–	–	–	–
Speed limit indicator (1 if 60 mph, 0 otherwise)	–	–	–	–	–	–	1.670	2.89	0.643	4.23
SC indicator (1 if SC, 0 otherwise)	–	–	–	–	1.145	3.34	1.225	2.55	0.320	2.61
<i>SD of parameter density function</i>	–	–	–	–	2.938	3.80	3.264	2.88	–	–
Urban area indicator (1 if the crash occurred in an urban area, 0 otherwise)	-1.969	-4.31	-0.584	-5.84	-1.829	-3.66	-0.847	-2.49	-0.615	-5.20
<i>SD of parameter density function</i>	–	–	–	–	2.356	2.90	–	–	–	–
Vehicle characteristics										
Motorcycle preceding collision (1 if straight, 0 otherwise)	–	–	0.158	1.91	–	–	0.680	2.10	0.367	3.84
Vehicle preceding collision (1 if straight, 0 otherwise)	–	–	0.286	3.30	1.342	3.88	0.645	1.76	0.202	2.12
<i>SD of parameter density function</i>	–	–	–	–	–	–	3.007	2.59	–	–
Young-age motorcycle (1 if <6, 0 otherwise)	–	–	–	–	-0.788	-2.61	-1.505	-2.40	-0.268	-2.93
<i>SD of parameter density function</i>	–	–	–	–	2.428	3.29	2.212	2.36	–	–
Middle-age motorcycle (1 if 6–11, 0 otherwise)	–	–	–	–	-1.526	-3.66	-1.299	-2.31	–	–
<i>SD of parameter density function</i>	–	–	–	–	–	–	2.350	2.21	–	–
Old-age motorcycle (1 if >11, 0 otherwise)	1.061	2.96	–	–	–	–	–	–	–	–
Middle-age vehicle (1 if 6–11, 0 otherwise)	0.711	2.78	–	–	–	–	–	–	–	–
<i>SD of parameter density function</i>	1.231	2.22	–	–	–	–	–	–	–	–
Old-age vehicle (1 if >11, 0 otherwise)	0.688	2.82	–	–	–	–	–	–	–	–
Truck (1 if truck, 0 otherwise)	–	–	–	–	0.788	1.68	–	–	–	–
<i>SD of parameter density function</i>	–	–	–	–	2.094	2.58	–	–	–	–
Collision Type										
Head-on (1 if head-on, 0 otherwise)	0.592	1.65	–	–	1.140	2.47	–	–	–	–
<i>SD of parameter density function</i>	3.595	4.36	–	–	1.564	3.10	–	–	–	–
Sideswipe (1 if sideswipe, 0 otherwise)	–	–	–	–	1.622	2.58	–	–	–	–
<i>SD of parameter density function</i>	–	–	–	–	4.451	3.89	–	–	–	–
Rear-end (1 if rear-end, 0 otherwise)	–	–	–	–	1.467	3.23	–	–	–	–
Temporal variables										
Time indicator (1 if evening off-peak hours, 0 otherwise)	–	–	–	–	–	–	–	–	0.498	2.32
Weekday indicator (1 if Monday, 0 otherwise)	0.596	2.11	–	–	–	–	–	–	–	–
Weekday indicator (1 if Wednesday, 0 otherwise)	–	–	–	–	–	–	-1.949	-2.25	–	–
<i>SD of parameter density function</i>	–	–	–	–	–	–	4.575	3.23	–	–
Weekday indicator (1 if Thursday, 0 otherwise)	–	–	–	–	–	–	-1.704	-1.53	–	–
Weekday indicator (1 if Saturday, 0 otherwise)	-0.506	-2.03	–	–	–	–	–	–	–	–
μ	2.054	9.16	1.152	8.80	1.875	11.49	2.209	7.60	1.461	15.33
<i>SD of parameter density function</i>	0.391	3.44	–	–	0.204	2.32	0.823	3.49	–	–
Threshold covariates										
Weekday indicator (1 if Thursday, 0 otherwise)	0.301	3.10	–	–	–	–	0.620	2.15	–	–
Weekday indicator (1 if Saturday, 0 otherwise)	0.278	2.35	–	–	–	–	–	–	–	–
Old-age MC indicator (1 if >55, 0 otherwise)	0.457	5.18	–	–	–	–	–	–	–	–
Urban area indicator (1 if the crash occurred in an urban area, 0 otherwise)	–	–	0.273	2.82	–	–	–	–	–	–
Motorcycle preceding collision (1 if straight, 0 otherwise)	–	–	-0.241	-2.23	–	–	–	–	-0.205	-2.06
Young-age MC indicator (1 if <25, 0 otherwise)	–	–	0.330	3.16	–	–	–	–	–	–
Passenger car (1 if passenger car, 0 otherwise)	–	–	0.248	2.34	–	–	–	–	–	–
Head-on (1 if head-on, 0 otherwise)	–	–	-0.259	-2.79	–	–	–	–	–	–
Young-age vehicle (1 if <6, 0 otherwise)	–	–	-0.163	-1.77	–	–	–	–	–	–
Middle-age motorcycle (1 if 6–11, 0 otherwise)	–	–	–	–	-0.290	-3.25	–	–	–	–
Sideswipe (1 if sideswipe, 0 otherwise)	–	–	–	–	0.551	7.81	–	–	–	–
Speed limit indicator (1 if 60 mph, 0 otherwise)	–	–	–	–	–	–	–	–	-0.285	-3.21
Number of parameters (K)	43		20		43		31		14	
Number of observations (N)	5305		3116		3252		1872		2296	
Log-likelihood at zero	-3123.198		-2186.012		-2288.212		-1294.613		-1725.696	
Log-likelihood at convergence	-3077.717		-2054.615		-2226.146		-1270.277		-1607.764	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.015		0.060		0.027		0.019		0.068	
Akaike information criterion (AIC)	6241.434		4149.230		4538.292		2602.554		3243.528	
Bayesian information criterion (BIC)	6524.219		4270.116		4800.034		2774.132		3323.873	

^aMC = motorcyclist, SC = single carriageway, and SD = standard deviation. Ages are in years.^bA dash means that the corresponding variable is not significant.

Table 9. Comparison of the performance of the LCMLCP model and RTRPGOL models.

Model	Evaluation index	2016	2017	2018	2019	2020
LCMLCP	Number of parameters (K)	34	32	42	31	26
	Number of observations (N)	5305	3116	3252	1872	2296
	Log-likelihood at zero	-5828.138	-3423.276	-3572.687	-2056.602	-2522.414
	Log-likelihood at convergence	-3090.805	-2028.373	-2243.256	-1266.06	-1582.151
	$\rho^2 = 1 - LL(\beta)/LL(0)$	0.470	0.407	0.372	0.384	0.373
	Akaike information criterion (AIC)	6249.610	4120.746	4570.512	2594.120	3216.302
	Bayesian information criterion (BIC)	6473.208	4314.164	4826.167	2765.698	3365.514
RTRPGOL	Number of parameters (K)	43	20	43	31	14
	Number of observations (N)	5305	3116	3252	1872	2296
	Log-likelihood at zero	-3123.198	-2186.012	-2288.212	-1294.613	-1725.696
	Log-likelihood at convergence	-3077.717	-2054.615	-2226.146	-1270.277	-1607.764
	$\rho^2 = 1 - LL(\beta)/LL(0)$	0.015	0.060	0.027	0.019	0.068
	Akaike information criterion (AIC)	6241.434	4149.230	4538.292	2602.554	3243.528
	Bayesian information criterion (BIC)	6524.219	4270.116	4800.034	2774.132	3323.873

Table 10. The impact trend of determinants in the LCMLCP model and RTRPGOL models.

Determinants	LCMLCP					RTRPGOL				
	2016	2017	2018	2019	2020	2016	2017	2018	2019	2020
Motorcyclist characteristics										
Male MC indicator (1 if male, 0 otherwise)	- ^a	↓ ↑ ↑	↓ ↑ ↑	-	↓ ↑ ↑	-	↓ ↑ ↑	↓ ↑ ↑	-	↓ ↑ ↑
Young-age MC indicator (1 if < 25, 0 otherwise)	↑ ↓ ↑	↓ ↑ ↑	↑ ↓ ↓	-	↑ ↓ ↑	↑ ↓ ↓	↓ ↑ ↑	↑ ↓ ↓	-	↑ ↓ ↓
Middle-age MC indicator (1 if 25-55, 0 otherwise)	↓ ↓ ↓	-	↑ ↓ ↓	-	-	-	-	↑ ↓ ↓	-	-
Old-age MC indicator (1 if > 55, 0 otherwise)	-	-	-	-	-	↓ ↑ ↑	-	-	-	-
Urban MC indicator (1 if motorcyclist is from an urban area, 0 otherwise)	↑ ↓ ↓	-	-	-	-	-	-	-	-	-
Driver characteristics										
Male driver indicator (1 if male, 0 otherwise)	-	↓ ↑ ↑	-	-	-	-	↓ ↑ ↑	-	-	-
Young-age driver indicator (1 if < 25, 0 otherwise)	-	-	-	↓ ↑ ↑	-	-	-	-	-	↑ ↓ ↓
Old-age driver indicator (1 if > 65, 0 otherwise)	-	-	-	-	-	↓ ↑ ↑	-	↓ ↑ ↑	-	-
Roadway and environmental conditions										
Weather condition indicator (1 if fine, 0 otherwise)	-	↓ ↑ ↑	↓ ↑ ↑	↑ ↓ ↑	-	-	↓ ↑ ↑	↓ ↑ ↑	↓ ↑ ↑	-
Darkness with street light indicator (1 if darkness with street light, 0 otherwise)	-	↓ ↓ ↓	-	-	-	-	-	-	-	-
Speed limit indicator (1 if 30 mph, 0 otherwise)	↑ ↓ ↑	↑ ↓ ↓	↑ ↑ ↓	-	↓ ↑ ↓	↑ ↓ ↓	↑ ↓ ↓	↑ ↓ ↓	-	↓ ↑ ↑
Speed limit indicator (1 if 60 mph, 0 otherwise)	-	-	-	↓ ↑ ↑	↑ ↓ ↑	-	-	-	↓ ↑ ↑	↓ ↑ ↑
SC indicator (1 if SC, 0 otherwise)	-	-	-	-	↓ ↓ ↑	↓ ↑ ↑	-	↓ ↑ ↑	↓ ↑ ↑	↓ ↑ ↑
DC indicator (1 if DC, 0 otherwise)	-	-	↓ ↑ ↑	-	-	-	-	-	-	-
Urban area indicator (1 if the crash occurred in an urban area, 0 otherwise)	↑ ↓ ↓	↑ ↓ ↓	↑ ↓ ↓	↑ ↓ ↓	↑ ↓ ↓	↑ ↓ ↓	↑ ↓ ↓	↑ ↓ ↓	↑ ↓ ↓	↑ ↓ ↓
Vehicle characteristics										
MC preceding collision (1 if straight, 0 otherwise)	-	↓ ↑ ↑	↓ ↓ ↑	-	↓ ↑ ↑	-	↓ ↑ ↑	↓ ↑ ↑	↓ ↑ ↑	↓ ↑ ↑
Vehicle preceding collision (1 if straight, 0 otherwise)	-	↑ ↑ ↑	↑ ↑ ↑	↓ ↑ ↑	↓ ↓ ↑	↓ ↑ ↑	↓ ↑ ↑	↓ ↑ ↑	↓ ↑ ↑	↓ ↑ ↑
Young-age MC (1 if < 6, 0 otherwise)	-	↑ ↓ ↓	↑ ↓ ↓	↑ ↓ ↓	-	-	-	↑ ↓ ↓	↑ ↓ ↓	↑ ↓ ↓
Middle-age MC (1 if 6-11, 0 otherwise)	↓ ↑ ↑	-	↑ ↓ ↑	↑ ↓ ↑	-	-	-	↑ ↓ ↓	↑ ↓ ↓	-
Older MC (1 if > 11, 0 otherwise)	-	-	-	-	-	↓ ↑ ↑	-	-	-	-
Young-age vehicle (1 if < 6, 0 otherwise)	-	-	-	-	-	-	↓ ↑ ↑	-	-	-
Middle-age vehicle (1 if 6-11, 0 otherwise)	-	-	-	-	-	↓ ↑ ↑	-	-	-	-
Older vehicle (1 if > 11, 0 otherwise)	↓ ↑ ↑	-	-	-	-	↓ ↑ ↑	-	-	-	-
Passenger car (1 if passenger car, 0 otherwise)	-	↑ ↑ ↓	-	↑ ↑ ↓	-	-	↓ ↑ ↑	-	↑ ↓ ↓	-
Truck (1 if truck, 0 otherwise)	-	-	↓ ↑ ↑	-	-	-	-	↓ ↑ ↑	-	-
Collision Type										
Head-on (1 if head-on, 0 otherwise)	↑ ↓ ↑	↓ ↑ ↑	↓ ↑ ↑	-	-	↓ ↑ ↑	↓ ↑ ↑	↓ ↑ ↑	-	-
Sideswipe (1 if sideswipe, 0 otherwise)	-	-	↓ ↑ ↑	-	-	-	-	↑ ↓ ↓	-	-
Rear-end (1 if rear-end, 0 otherwise)	↑ ↓ ↓	-	↓ ↑ ↓	-	-	↑ ↓ ↓	↓ ↑ ↑	↓ ↑ ↑	-	-
Temporal variables										
Time indicator (1 if morning peak hour, 0 otherwise)	-	-	-	-	↑ ↓ ↑	-	↓ ↑ ↑	-	↑ ↓ ↓	-
Time indicator (1 if evening off-peak hour, 0 otherwise)	-	-	-	-	-	↓ ↑ ↑	-	-	-	↓ ↑ ↑
Weekday indicator (1 if Monday, 0 otherwise)	-	-	↓ ↑ ↑	↓ ↓ ↑	-	↓ ↑ ↑	-	↓ ↑ ↑	-	-
Weekday indicator (1 if Tuesday, 0 otherwise)	↑ ↓ ↓	-	-	-	-	-	-	-	-	-
Weekday indicator (1 if Wednesday, 0 otherwise)	-	-	-	↑ ↓ ↓	-	-	-	-	↑ ↓ ↓	-
Weekday indicator (1 if Thursday, 0 otherwise)	-	-	-	-	-	-	-	-	-	-
Weekday indicator (1 if Saturday, 0 otherwise)	↑ ↓ ↑	-	-	-	-	↑ ↓ ↓	-	-	-	-
Season indicator (1 if summer, 0 otherwise)	-	-	↓ ↑ ↓	-	-	↓ ↑ ↑	↓ ↑ ↑	↑ ↓ ↓	-	↑ ↓ ↓

A dash means that the corresponding variable is not significant. The direction of arrows represents the impact trend of the determinants on the three injury levels. For instance, the ↓↑↑ denotes this variable decreases the likelihood of minor injuries, while it increases the likelihood of severe injuries and fatal injuries.

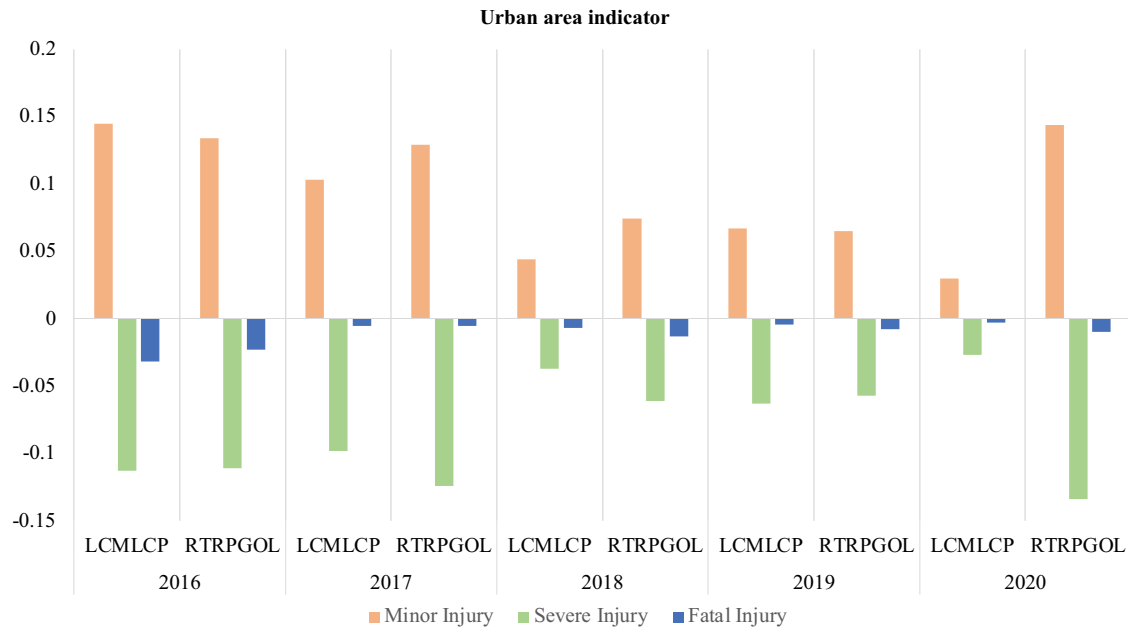


Figure 3. Marginal effects of Urban area indicator across 5 years: (2016–2020).

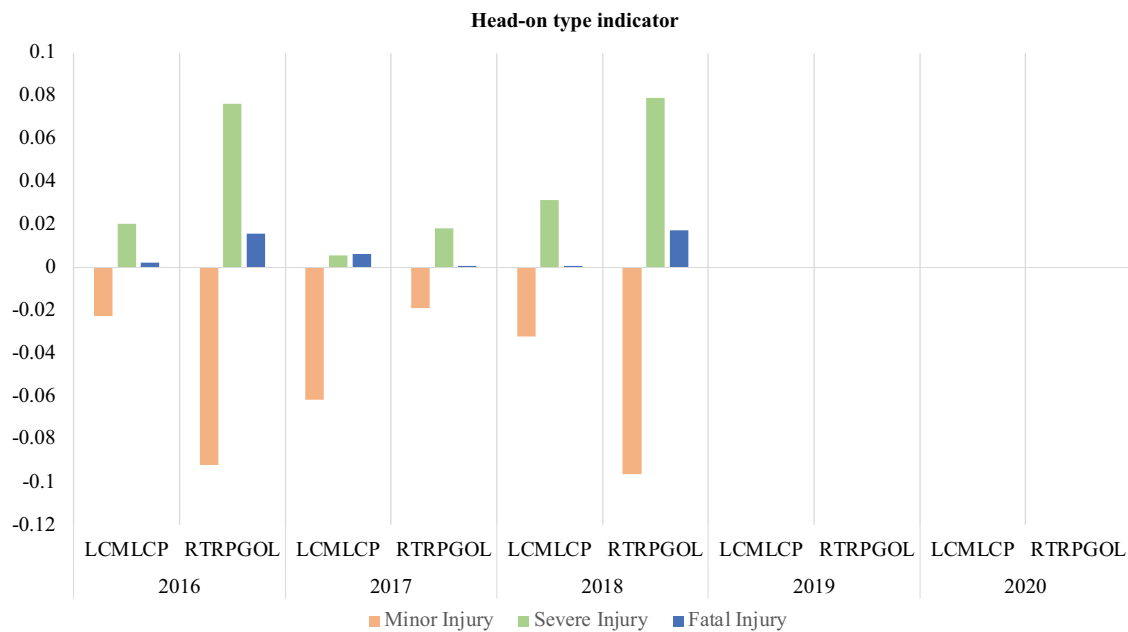


Figure 4. Marginal effects of head-on type indicator across 5 years: (2016–2020).

injuries and increased probabilities of minor injuries) for 2017–2020. Though showing temporal instability, the motorcycle age from 6 to 11 years consistently increased the fatal injury likelihood for 2016, 2018, and 2019. The critical elements might be the poor performance of middle-aged motorcyclists characterized by slippery tire surfaces, worse braking systems, and aging fuselages. Similarly, vehicles older than 11 years tend to increase the likelihood of severe and fatal injury in 2016. The usual maintenance of motorcycles and vehicles is critical for reducing injury severity.

Showing potential temporal instability, the passenger car colliding with motorcycles decreases the fatal injury likelihood by 0.0106 and 0.0093 for the 2017 and 2019 models, respectively. On the

contrary, the truck increases the severe/fatal injury likelihood by 0.0082/0.0023 for 2019.

Collision type

Regarding the collision type, head-on is found to increase the fatal injury likelihood for the 2016–2018 models. Thus, more education should be implemented to prevent risky driving behaviors like overtaking oppositely, and necessary guardrails are also essential for high-risk spots. The rear-end crashes tend to decrease the fatal injury likelihood for 2016 and 2018. This finding supports recent evidence (Se et al. 2022). Moreover, the sideswipe increases the severe/fatal injury likelihood by 0.0311/0.0020 for 2017.

Table 11. The combined marginal effects of determinants based on the LCMMLCP model for motorcycle-vehicle crashes.

Variable (LCMMLCP) ^a	Minor Injury					Severe Injury					Fatal Injury				
	2016	2017	2018	2019	2020	2016	2017	2018	2019	2020	2016	2017	2018	2019	2020
Motorcyclist characteristics															
[MI] Male MC indicator (1 if male, 0 otherwise)	-	-0.0725	-0.1137	-	-0.0807	-	0.0596	0.0886	-	0.0782	-	0.0129	0.0251	-	0.0025
[MI] Young-age MC indicator (1 if < 25, 0 otherwise)	0.2198	-	0.0352	-	0.0122	-0.2207	-	-0.0315	-	-0.0102	0.0009	-	-0.0037	-	0.0020
[FI] Young-age MC indicator (1 if < 25, 0 otherwise)	-	-0.0014	-	-	-	-	-0.0076	-	-	-	-	0.0090	-	-	-
[MI] Middle-age MC indicator (1 if 25–55, 0 otherwise)	-	-	0.0421	-	-	-	-	-0.0398	-	-	-	-	-0.0023	-	-
[SI] Middle-age MC indicator (1 if 25–55, 0 otherwise)	-0.0061	-	-	-	-	0.0065	-	-	-	-	-0.0004	-	-	-	-
[MI] Urban MC indicator (1 if motorcyclist is from an urban area, 0 otherwise)	0.0406	-	-	-	-0.0390	-	-	-	-	-	-0.0016	-	-	-	-
Driver characteristics															
[MI] Male driver indicator (1 if male, 0 otherwise)	-	-0.0333	-	-	-	-	0.0304	-	-	-	-	0.0029	-	-	-
[MI] Young-age driver indicator (1 if < 25, 0 otherwise)	-	-	-	-0.1002	-	-	-	-	0.0951	-	-	-	-	0.0048	-
Roadway and Environmental Conditions															
[MI] Weather condition indicator (1 if fine, 0 otherwise)	-	-0.3358	-0.0439	0.0158	-	-	0.1979	0.0416	-0.0224	-	-	0.1379	0.0023	0.0066	-
[FI] Darkness with street light indicator (1 if darkness with street light, 0 otherwise)	-	-0.0013	-	-	-	-	-0.0006	-	-	-	-	0.0019	-	-	-
[MI] Speed limit indicator (1 if 30 mph, 0 otherwise)	0.0074	-	-	-	-0.0280	-0.0084	-	-	-	0.0284	0.0010	-	-	-	-0.0004
[FI] Speed limit indicator (1 if 30 mph, 0 otherwise)	-	0.0028	0.0024	-	-	-	0.0005	0.0005	-	-	-	-0.0033	-0.0029	-	-
[MI] Speed limit indicator (1 if 60 mph, 0 otherwise)	-	-	-	-0.0127	-	-	-	-	0.0110	-	-	-	-	0.0017	-
[SI] Speed limit indicator (1 if 60 mph, 0 otherwise)	-	-	-	-	0.0193	-	-	-	-	-0.0293	-	-	-	-	0.0100
[SI] SC indicator (1 if SC, 0 otherwise)	-	-	-	-	0.0170	-	-	-	-	-0.0232	-	-	-	-	0.0062
[FI] SC indicator (1 if SC, 0 otherwise)	-	-	-	-	-0.1416	-	-	-	-	-0.0980	-	-	-	-	0.1121
[MI] DC indicator (1 if DC, 0 otherwise)	-	-	-0.0832	-	-	-	-	0.0741	-	-	-	-	0.0091	-	-
[MI] Urban area indicator (1 if the crash occurred in an urban area, 0 otherwise)	0.1444	0.1031	0.0440	0.0668	0.0298	-0.1128	-0.0979	-0.0371	-0.0627	-0.0270	-0.0316	-0.0052	-0.0069	-0.0041	-0.0028
Vehicle characteristics															
[MI] MC preceding collision (1 if straight, 0 otherwise)	-	-0.0259	-	-	-0.0333	-	0.0164	-	-	0.0328	-	0.0095	-	-	0.0005
[FI] MC preceding collision (1 if straight, 0 otherwise)	-	-	-0.0082	-	-	-	-	-0.0033	-	-	-	-	0.0115	-	-
[MI] Vehicle preceding collision (1 if straight, 0 otherwise)	-	-0.0200	-0.0357	-	-	-	0.0176	0.0263	-	-	0.0024	0.0094	-	-	-
[SI] Vehicle preceding collision (1 if straight, 0 otherwise)	-	-	-	-0.0217	-	-	-	-	-0.0370	-	-	-	0.0587	-	-
[FI] Vehicle preceding collision (1 if straight, 0 otherwise)	-	-	-	-0.0066	-0.0142	-	-	-	0.0501	-0.0100	-	-	-	-0.0435	0.0242
[MI] Young-age MC (1 if < 6, 0 otherwise)	-	-	-	-	0.0270	-	-	-	-0.0267	-	-	-	-	-0.0003	-
[SI] Young-age MC (1 if < 6, 0 otherwise)	-	-	0.0275	0.0066	-	-	-0.0004	-	-0.0064	-	-	-	-0.0014	-0.0002	-
[FI] Young-age MC (1 if < 6, 0 otherwise)	-	0.0057	-	-	-	-	-	-	-	-	-0.0053	-	-	-	-
[MI] Middle-age MC (1 if 6–11, 0 otherwise)	-0.0091	-	-	-	0.0077	-	-	-	-	0.0014	-	-	-	-	-
[SI] Middle-age MC (1 if 6–11, 0 otherwise)	-	-	0.0185	0.0062	-	-	-	-0.0195	-0.0073	-	0.0001	-	-	-	-
[SI] Older vehicle (1 if > 11, 0 otherwise)	-0.0085	-	-	-	0.0084	-	0.0045	-	-	-	-	-0.106	-	-0.0093	-
[FI] Passenger car (1 if passenger car, 0 otherwise)	-	0.0061	-	-	-	-	-	-	0.0069	-	-	-	-	-	-
[MI] Truck (1 if truck, 0 otherwise)	-	-	-0.0105	-	-	-	-	0.0082	-	-	-	-	0.0023	-	-
Collision Type															
[MI] Head-on (1 if head-on, 0 otherwise)	-0.0225	-0.0617	-0.0321	-	-	0.0204	0.0056	0.0313	-	-	0.0021	0.0061	0.0008	-	-
[SI] Head-on (1 if head-on, 0 otherwise)	0.0313	-	-	-	-0.0383	-	-	-	-	-	0.0070	-	-	-	-
[SI] Sideswipe (1 if sideswipe, 0 otherwise)	-	-	-0.0291	-	-	-	-	0.0311	-	-	-	-	0.0020	-	-
[MI] Rear-end (1 if rear-end, 0 otherwise)	0.0102	-	-	-	-0.0101	-	-	-	-	-	-0.0001	-	-	-	-
[SI] Rear-end (1 if rear-end, 0 otherwise)	-	-	-0.0434	-	-	-	-	0.0457	-	-	-	-	-0.0023	-	-
Temporal variables															
[MI] Time indicator (1 if morning peak hour, 0 otherwise)	-	-	-	0.0162	-	-	-	-	-0.0103	-	-	-	-	-0.0059	-
[MI] Weekday indicator (1 if Monday, 0 otherwise)	-	-	-0.0123	-	-	-	-	0.0091	-	-	-	-	0.0023	-	-
[FI] Weekday indicator (1 if Monday, 0 otherwise)	-	-	-	-0.0013	-	-	-	-	-0.0028	-	-	-	-	0.0041	-
[MI] Weekday indicator (1 if Tuesday, 0 otherwise)	-	-	-	-	-	-0.0040	-	-	-	-	-0.0001	-	-	-	-
[MI] Weekday indicator (1 if Wednesday, 0 otherwise)	0.0041	-	-	0.0003	-	-	-	-	0.0003	-	-	-	-	-0.0006	-
[SI] Weekday indicator (1 if Saturday, 0 otherwise)	0.0594	-	-	-	-	-0.0617	-	-	-	-	0.0023	-	-	-	-
[FI] Weekday indicator (1 if Saturday, 0 otherwise)	0.0003	-	-	-	0.0011	-	-	-	-	-0.0013	-	-	-	-	-
[MI] Season indicator (1 if summer, 0 otherwise)	-	-	-0.0126	-	-	-	-	0.0163	-	-	-	-	-0.0037	-	-

^aMC = motorcyclist, SC = single carriageway, and DC = dual carriageway. Ages are in years.

Table 12. Average marginal effects of determinants based on the RTRPGOL model for motorcycle-vehicle crashes.

Variable (RTRPGOL) ^a	Minor Injury				Severe Injury				Fatal Injury						
	2016	2017	2018	2019	2020	2016	2017	2018	2019	2020	2016	2017	2018	2019	2020
Motorcyclist characteristics															
Male MC indicator (1 if male, 0 otherwise)	-	-0.0830	-0.1053	-	-0.1128	-	0.0802	0.0865	-	0.1066	-	0.0028	0.0188	-	0.0062
Young-age MC indicator (1 if < 25, 0 otherwise)	0.0198	-0.0134	0.1291	-	0.0605	-0.0164	0.0129	-0.1060	-	-0.0567	-0.0034	0.0005	-0.0231	-	-0.0038
Middle-age MC indicator (1 if 25–55, 0 otherwise)	-	-	0.1138	-	-	-	-	-0.0934	-	-	-	-	-0.0204	-	-
Old-age MC indicator (1 if > 55, 0 otherwise)	-0.0534	-	-	-	-	0.0442	-	-	-	-	0.0092	-	-	-	-
Urban MC indicator (1 if motorcyclist is from an urban area, 0 otherwise)	0.0302	-	-	-	-0.0250	-	-	-	-	-0.0052	-	-	-	-	-
Driver characteristics															
Male driver indicator (1 if male, 0 otherwise)	-	-0.0447	-	-	-	-	0.0430	-	-	-	-	0.0017	-	-	-
Young-age driver indicator (1 if < 25, 0 otherwise)	-	-	-	0.2469	-	-	-	-	-0.2176	-	-	-	-	-0.0293	-
Old-age driver indicator (1 if > 65, 0 otherwise)	-0.0075	-	-0.0185	-	-	0.0062	-	0.0152	-	-	0.0012	-	0.0033	-	-
Roadway and environmental conditions															
Weather condition indicator (1 if fine, 0 otherwise)	-	-0.0939	-0.0697	-0.0340	-	-	0.0906	0.0572	0.0300	-	-	0.0033	0.0125	0.0040	-
Speed limit indicator (1 if 30 mph, 0 otherwise)	0.0478	0.0794	0.0734	-	-0.0109	-0.0396	-0.0763	-0.0603	-	0.0102	-0.0082	-0.0031	-0.0131	-	0.0007
Speed limit indicator (1 if 60 mph, 0 otherwise)	-	-	-0.1277	-0.1544	-	-	-	-	0.1126	0.1426	-	-	0.0151	0.0118	-
SC indicator (1 if SC, 0 otherwise)	-0.0371	-	-0.1033	-0.0937	-0.0716	0.0307	-	0.0848	0.0826	0.0673	0.0063	-	0.0185	0.0110	0.0043
Urban area indicator (1 if the crash occurred in an urban area, 0 otherwise)	0.1340	0.1290	0.0743	0.0648	0.1438	-0.1110	-0.1238	-0.0610	-0.0571	-0.1339	-0.0230	-0.0052	-0.0133	-0.0076	-0.0099
Vehicle characteristics															
MC preceding collision (1 if straight, 0 otherwise)	-	-0.0337	-0.0652	-0.0520	-0.0834	-	0.0324	0.0535	0.0458	0.0782	-	0.0013	0.0116	0.0061	0.0052
Vehicle preceding collision (1 if straight, 0 otherwise)	-0.0300	-0.0623	-0.0722	-0.0493	-0.0469	0.0248	0.0599	0.0435	0.0439	0.0439	0.0051	0.0024	0.0129	0.0058	0.003
Young-age MC (1 if < 6, 0 otherwise)	-	-	0.0797	0.1151	0.0614	-	-	-0.0655	-0.1015	-0.0575	-	-	-0.0142	-0.0136	-0.0039
Middle-age MC (1 if 6–11, 0 otherwise)	-	-	0.0863	0.0994	-	-	-	-0.0709	-0.0876	-	-	-	-0.0154	-0.0117	-
Older MC (1 if > 11, 0 otherwise)	-0.0400	-	-	-	-	0.0332	-	-	-	-	0.0068	-	-	-	-
Young-age vehicle (1 if < 6, 0 otherwise)	-	-0.0161	-	-	-	-	0.0155	-	-	-	-	0.0006	-	-	-
Middle-age vehicle (1 if 6–11, 0 otherwise)	-0.0509	-	-	-	-	0.0422	-	-	-	-	0.0087	-	-	-	-
Old-age vehicle (1 if > 11, 0 otherwise)	-0.0349	-	-	-	-	0.0289	-	-	-	-	0.0060	-	-	-	-
Passenger car (1 if passenger car, 0 otherwise)	-	-0.0012	-	0.0376	-	-	0.0012	-	-0.0331	-	-	0.000	-	-0.0045	-
Truck (1 if truck, 0 otherwise)	-	-	-0.0494	-	-	-	-	0.0406	-	-	-	-	0.0088	-	-
Collision Type															
Head-on (1 if head-on, 0 otherwise)	-0.0921	-0.0189	-0.0963	-	-	0.0762	0.0182	0.0791	-	-	0.0158	0.0007	0.0172	-	-
Sideswipe (1 if sideswipe, 0 otherwise)	-	-	0.0125	-	-	-	-	-0.0103	-	-	-	-	-0.0022	-	-
Rear-end (1 if rear-end, 0 otherwise)	0.0165	-0.0830	-0.1054	-	-	-0.0136	0.0802	0.0865	-	-	-0.0028	0.0028	0.0188	-	-
Temporal variables															
Time indicator (1 if morning peak hour, 0 otherwise)	-	-0.0134	-	0.0439	-	-	0.0129	-	-0.0387	-	-	0.0005	-	-0.0052	-
Time indicator (1 if evening off-peak hour, 0 otherwise)	-0.0412	-	-	-0.1204	-	0.0341	-	-	-	0.1112	0.0070	-	-	-	0.0092
Weekday indicator (1 if Monday, 0 otherwise)	-0.0095	-	-0.0209	-	-	0.0079	-	0.0171	-	-	0.0016	-	0.0037	-	-
Weekday indicator (1 if Wednesday, 0 otherwise)	-	-	-	0.1491	-	-	-	-	-0.1315	-	-	-	-	-0.0176	-
Weekday indicator (1 if Thursday, 0 otherwise)	-0.0027	-	-	0.0263	-0.1128	0.0022	-	-	-0.0232	0.1066	0.0004	-	-	-0.0031	0.0062
Weekday indicator (1 if Saturday, 0 otherwise)	0.0276	-	-	-	-0.0228	-	-	-	-	-	-0.0047	-	-	-	-
Season indicator (1 if summer, 0 otherwise)	-0.0082	-0.0447	0.0057	-	0.0605	0.0068	0.043	-0.0047	-	-0.0567	0.0014	0.0017	-0.0010	-	-0.0038

^aMC = motorcyclists, SC = single carriageway, and DC = dual carriageway. Ages are in age.

Temporal variables

The severe/fatal injury likelihood is decreased by 0.0103/0.0059 during the morning peak hours for 2019. This phenomenon might result from the risk compensation under low visibility or less riding of motorcyclists before dawn. Monday also increases the fatal injury likelihood by 0.0023 and 0.0041 for 2018 and 2019, respectively. Tuesday and Wednesday being significant for 2016 and 2019, respectively, show negative effects on the fatal injury likelihood. Saturday is statistically significant for 2016, with the average marginal effects indicating an increased likelihood of fatal injuries. The potential reason might be the involvement of alcohol, small traffic volumes, and purposes of travel during weekends (Se et al. 2022). Moreover, the summer is significant for 2018, increasing the probability of severe injuries by 0.0163, showing the same findings as recent studies (Jung, Xiao, and Yoon 2013).

Practical applications

The critical factors increasing the risk outcomes include male motorcyclists, higher speed limits, older ages of motorcyclists and vehicles, fine weather, single carriageways, and head-on collision types, as shown in Table 10. Based on these findings concerning the determinants, more effective countermeasures can be developed to reduce motorcyclists' injury severity when involved in crashes with vehicles. The practical implications are as follows:

- (1) *Enhancing Enforcement and Education Programs for Male Motorcyclists.* Male motorcyclists are more likely to engage in dangerous driving behaviors such as speeding, riding under the influence of alcohol, and casual riding. Therefore, targeted enforcement and education programs for this group are crucial.
- (2) *Addressing Potential Threats from Male and Elderly Drivers.* Male and elderly drivers who collide with motorcycles pose significant threats to motorcyclists. Consequently, it is imperative to implement enforcement and education programs specifically for these drivers.
- (3) *Implementing Strict Rules for Regular Checks and Maintenance.* Regular inspections and maintenance of motorcycles and vehicles are recommended. Poor braking performance in older motorcycles and vehicles can lead to severe consequences.
- (4) *Enforcing Strict Separation Zones.* Strict separation zones should be implemented to prevent motorcyclists from illegally driving, especially on single-carriageways. This includes ensuring compliance with right-of-way, stop signs, and road markings.
- (5) *Addressing Higher Speed Limits.* Higher speed limits increase the severity of injuries in motorcycle-involved accidents. Motorcyclists who frequently ride on roads with high-speed limits should be required to wear safety gear and maintain a greater distance from other vehicles.
- (6) *Enhancing Awareness and Deployment of Safety Systems.* Attention should be paid to scenarios where side impacts are likely, such as when a car might collide with the side of a motorcycle while pulling over. It is recommended to encourage manufacturers to widely deploy the Lane Change Alert with the Side Blind Zone Alert system in their vehicles.

Conclusions

Using motorcycle-vehicle crashes in the UK from 2016 to 2020, this paper has estimated two logit models to reveal the transferability of determinants affecting motorcyclists' injury outcomes in motorcycle-vehicle collisions in the five years. The models were the latent class multinomial logit with class probability model and the random thresholds-parameters generalized ordered logit model. Three possible injury severity levels (fatal injury, severe injury, and minor injury) are considered in this study. The main conclusions of the study are as follows:

- (1) Among the characteristics of the motorcyclist, driver, roadway, environment, vehicle, and collision, multiple variables affect motorcyclists' injury severities in the two models. The LCMLCP model slightly outperforms the RTRPGOL model regarding the goodness-of-fit measures (except for 2016 and 2018), reflecting the factors having uncertainty and variability over time from the side. Nonetheless, it is noted that the LCMLCP models provide higher ρ^2 than the RTRPGOL models in all years. The differences in the estimation results were caused by the differences in the frameworks and the unobserved heterogeneities captured by the different estimation mechanisms of the two models.
- (2) Even with variations in the effects of a specific variable, the findings regarding the temporal shifts are consistent in parameter estimates through the applied models. The robust results indicate that these determinants vary over time, while the temporal instability is confirmed by the likelihood ratio tests and out-of-sample predictions in both heterogeneity modeling approaches. Otherwise, the marginal effects also reflect the temporal shifts in influence trend and degree. Moreover, the RTRPGOL models tend to have more variability in marginal effects over time and larger differences in out-of-sample predictions relative to the LCMLCP models.
- (3) In addition to the motorcyclist-related variables, other motorized vehicle-related factors were also found to be significant. Specifically, variables such as male driver, older driver, vehicle preceding collision, and truck were associated with an increased likelihood of fatal and severe injuries, despite exhibiting temporal instability. These insights extend our understanding of how different motorized vehicle dynamics impact the injury severity outcomes of motorcyclists. This broader perspective highlights the interconnected nature of road safety, emphasizing the need to consider a wide range of influencing factors beyond the motorcyclist alone. Such comprehensive findings can inform targeted interventions and policies to reduce severe injuries and fatalities among motorcyclists.
- (4) This study has some limitations. While year-wise models are valuable for crash severity prediction, their predictive power may be affected by annual fluctuations in variable effects due to changes in external conditions, driver behavior, or crash subpopulations. Additionally, data-specific biases, such as omitting no-injury crashes, may introduce unobserved heterogeneity. To enhance robustness, a hybrid framework incorporating rolling forecasts, Bayesian hierarchical models, and multi-year aggregation could mitigate temporal inconsistencies. A pooled model integrating all datasets may also offer a more parsimonious structure. Nevertheless, using year-wise latent class models provides insights into unobserved heterogeneities, and future research should

explore comprehensive datasets and advanced methodologies to improve predictive stability and policy relevance.

Notes

1. The number of degrees of freedom is equal to the sum of the statistically significant parameters in the separate model excluding the number of statistically significant parameters in the joint model (Washington et al. 2020).
2. This test is also conducted with the y_1 and y_2 subgroups being reversed to obtain the two-test results for each model.
3. It should be noted that the thresholds are found to be fixed in the 2017 and 2020 models, so that the fixed thresholds random parameters generalized ordered logit models are applied for 2017 and 2020 models.
4. As the base framework of the RTRPGOL models, OL and GOL are also estimated. After extensively testing for different nesting structures for OL and GOL models, we find that these models collapsed to the RTRPGOL model. Again, it should be noted that the thresholds are found to be fixed in the 2017 and 2020 models, so that the RPGOL models are applied for 2017 and 2020.
5. As shown in Tables 11 and 12, the marginal effects of urban area indicator in the LCMLCP model are almost 3.5 ~ 5 times higher than those in the RTRPGOL model. Besides, the marginal effects based on the two models across 2016–2019 are similar.

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ORCID

Chenzhu Wang  <http://orcid.org/0000-0001-8242-148X>

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