

Research Article

Modeling the Motorcycle Crash Severity on Nonintersection Urban Roadways in the Australian State of Victoria Using a Random Parameters Logit Model

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Due to a lack of physical protection and balance, motorcycle riders are one of the most vulnerable road users and are more likely to suffer severe injuries than motorists. Between 2009 and 2020, about 60% of motorcycle crashes occurred on nonintersection urban roadways in Victoria, Australia. While considerable research on intersections and their influence on the severity of motorcycle crashes has been conducted, there are limited studies on motorcycle crashes on nonintersection roadways. Since gathering all information from every motorcycle crash may not be possible, heterogeneity can arise from unobserved factors and cause problems in developing reliable crash severity models. Therefore, this study aims to investigate the factors contributing to motorcycle crash severity on Victorian nonintersection urban roadways while considering the heterogeneity of factors. A total of 10,897 nonintersection motorcycle crash data from the beginning of 2009 to November 2020 in the State of Victoria, Australia, were analyzed. A random parameters (mixed) logit model (RPL) was used for evaluating motorcycle crashes. The severity of motorcycle crashes was divided into three categories: fatal injury, serious injury, and minor injury. Also, marginal effects were calculated to see how each parameter estimate affects crash severity outcomes. The RPL model results showed that some factors increased the likelihood of fatal injuries. These factors included not wearing a helmet, being in the older rider age group, riding during the early morning or midnight hours, weekend motorcycle use, riding in the early morning or midnight hours (00:00–6:29 A.M.), and insufficient lighting (dark and dusk/dawn). Also, the following factors enhanced the probability of serious injuries: having a pillion passenger, having a motorcycle age of more than 7 years, riding at higher speed limits (more than 50 km/h) or during peak hours in the morning (6:30–8:59 A.M.), and being in the younger age group (less than 26 years old). The findings from this study are valuable resources for road safety policy managers to develop effective strategies for improving motorcyclists' safety at nonintersections. This may include improving the light conditions at nonintersection, encouraging the motorcyclist to maintain motorcycles regularly, and educating the motorcyclist to wear a helmet, avoid distractions, and ride responsibly on the weekends.

1. Introduction

Traffic crashes have caused notable financial, physical, and emotional pain for families and society. Every year, nearly 1.3 million people are killed and 20 to 50 million people are injured in road crashes worldwide. About 0.65 million of those fatalities are vulnerable road users, including

motorcyclists, cyclists, and pedestrians [1]. Road traffic crash fatalities are forecasted to be the third leading cause of mortality by 2030 [2]. The safety of vulnerable road users has received more attention recently and is seen as an important social concern. As a result, considerable efforts are needed to improve the safety of vulnerable road users, including motorcycles [3].

Motorcycles are less expensive vehicles to acquire and ride than others, especially when fuel costs are high [4]. Further, motorcycles' mobility benefits, like their small size [5], make them a practical choice in congested urban areas with limited space. Their popularity as recreational vehicles [6] and easy maneuverability [7] have made them an economical and affordable mode of transport. In recent years, demand for motorcycles has increased in Australia and its southeastern State of Victoria. Indeed, motorcycle and scooter sales in Australia climbed by 6.2% in 2020, reaching 87,453 units, the largest in the previous five years. The upward trend continued in 2021 [8].

Motorcyclists are considered vulnerable road users, and they are more prone to fatal or serious injury due to a lack of physical protection for the rider [9] and less conspicuity [10] than other motorized vehicles. Considering per vehicle mile traveled in 2020, motorcyclists were approximately 28 times more likely than passenger car occupants to die in a motor vehicle crash and were four times more likely to be injured [11].

In 2019, an average of 10% of persons in the State of Victoria, Australia, held a motorcycle licence, while motorcyclists or pillion passengers were involved in around 17% of fatal crashes. In addition, compared to 2018, there was a 25% rise in crashes and fatalities in 2019. However, the increasing trend in the number of crashes in 2020 compared to 2019 decreased (it may be due to Victoria's strict COVID-19 lockdown in 2020), but it continued to increase in 2021 compared to 2020. Motorcycle crashes increased faster than all other road users in this state from 2020 to 2021 [8].

One of the challenges in the traffic safety domain is to minimize the number of fatalities and injuries and lessen crash severity levels. Several modeling approaches have been used in recent decades to predict the severity of motorcyclist injuries. The majority of the literature looked at the severity of the crash by categorizing the causes into the follows: human factors such as the rider's sociodemographic characteristics, vehicle features such as motorcycle age or size, environmental conditions such as weather conditions, roadway characteristics such as the width of the lane or median, and crash attribute such as the type of collision [12, 13].

The following factors were discovered to be linked with motorcyclist injury severity in past studies: not wearing a helmet [14–17]; riding in a high-speed limit zone [14–16]; age of motorcyclist [16, 17]; sex [12]; light condition [16, 18]; licence status [19]; intersection characteristics [20]; function of roadway [16, 21]; road geometry [22]; and presence of a pillion passenger [21].

Studies have yielded different outcomes regarding the importance of various contributing factors affecting a particular motorcycle crash type. The variances in driver behaviors, vehicle features, and traffic and road characteristics have been identified as reasons for these discrepancies. Further, the statistical procedures employed differ in various studies [9].

Some research focused solely on intersections, while others employed statistical models of discrete choice and machine learning models to investigate the contributing

variables. The authors in [23] examined motorcycle crashes at intersections in the State of Victoria between 2006 and 2018, taking into account the characteristics of different types of intersections. Various factors were considered in the study: motorcyclist age and sex, helmet use, certificate of status, weather, pavement conditions, lighting conditions, time of the crash, day of the crash, single-vehicle or multivehicle type crash, time of the crash, and impact and condition of the asphalt pavement. By using the multinomial logit model, the study concluded that motorcyclists with an age over 55, morning rush hour crashes, weekend crashes, midnight/early morning crashes, multivehicle crashes, *T*-intersections, crashes in towns and rural areas, stop or give-way intersections, roundabouts, and uncontrolled intersections increase the risk of fatal injury. In contrast, it was observed that female motorcyclists, snowy/stormy/foggy or wet weather, nighttime rush hours, and unpaved roads all reduced the risk of fatal motorcycle crashes and lowered mortality. While considerable research on intersections and their influence on the severity of motorcycle crashes has been conducted [24–26], there have been fewer studies on motorcycle crashes on nonintersection roadways. Paying more attention to crashes at intersections was not for motorcycles only. According to a study that investigated intersection and nonintersection crashes [27], 26% of private car intersection crashes were found to be severe, compared to 58.7% of nonintersection crashes. Also [28], claimed that the fatality rate of crashes that happened at nonintersection was substantially higher than the rate at the intersection. It is to be noted that about 60% of urban motorcycle crashes between 2009 and 2021 in the State of Victoria occurred in nonintersections [29].

Some of the factors influencing the likelihood of a crash and the severity of the resulting injury may not be available in a crash database. These variables (which comprise unobserved heterogeneity) can cause variance in the influence of observable variables on crash risk and severity [30]. As a result, a thorough investigation of the variables influencing the severity of motorcycle crashes, considering the heterogeneity of the parameters, is required.

This paper's main contribution lies in investigating the factors that contribute to the severity of motorcycle crashes on nonintersection urban roadways in Victoria while considering the heterogeneity of these factors. Non-intersection crashes refer to those that occur on any segment of a roadway or transportation facility that is not located at an intersection. The study's focus on considering the impact of heterogeneity by employing the random parameters logit model sets it apart from other works in the field. Neglecting to account for data heterogeneity in crash severity analysis can lead to biased outcomes, flawed conclusions, inaccurate safety policies, forecasting errors, and wastage of resources [31]. Therefore, the paper's contributions to the literature include exploring the influence of nonintersection urban factors on motorcycle crash severity and considering heterogeneity in the analysis to get accurate results. Several studies [32, 33] have demonstrated the strengths and accuracy of random parameter models in traffic crash analysis compared to the fixed-parameter model.

2. Methodology

The severity of crashes generally has discrete results. Therefore, statistical analysis, like discrete choice and econometric models, as well as conventional and practical machine learning methods [34], has been used to solve this problem. Among the discrete choice models, many studies have investigated the crash severity with various nominal or ordinal and ordered or unordered models, including probit and logit models [35].

Choosing an analytical model has always been difficult for traffic safety researchers since each model has benefits and drawbacks, requiring the researcher's ultimate decision to be based on the dataset's features [35]. For example, [36] found that when deciding between the ordered probit, random parameter logit (RPL), and multinomial logit (MNL) models, the RPL model is preferable when the sample size is large. Furthermore, RPL models outperformed MNL in terms of statistical performance with the same sample size [37]. Traditional crash severity studies are based on information gathered after a crash. In many aspects, this is quite restrictive. First, many minor crashes are not recorded, resulting in the loss of potentially crucial data and biasing the data towards the more recorded levels. Second, many significant factors that affect crash occurrence and severity (for example, vehicle speed, driver braking and maneuvering responses, etc.) are not recorded. This results in significant unobserved heterogeneity that affects the model and prevents important information from being used to make significant new inferences. Third, police-reported injury severity indicators (no injury, possible injury, obvious injury, crippling injury, fatality) are based on observations at the crash scene and are subject to change until a medical diagnosis is completed [38]. So, several unobserved factors influence the severity of individual crashes, and acquiring comprehensive data on each crash can be difficult or impossible. By avoiding those unobserved factors (also known as unobserved heterogeneity), it may result in erroneous parameter estimations and conclusions [30].

The MNL model was used by [15], who argued that MNL is an effective method for studying variables that contribute to the severity of motorcycling injuries. Since crash severity is frequently defined by natural ordering (from low to high severity), an ordered probability model, such as an ordered logit or ordered probit, may be suitable for analysis [39]. To account for the ordinal nature of the severity outcomes, researchers like [21] employed an ordered probit model to analyze injury severity and motorcycle damage severity in motorcycle crashes. The ordered models, however, have some drawbacks: The first issue is the underreporting of low-severity crashes like minor injury or property damage only (which is common in crash reports) which can lead to inaccuracies in parameter estimates or in ordered models. The second issue is that ordered models either raise the probability of fatality (and hence reduce the probability of minor injury) or reduce the probability of fatality (and subsequently increase the probability of minor injury). These models also can not consider a feature that raises or reduces both fatality and minor injury simultaneously [16]. As

a result, using an ordered model for all ordered data is not recommended [40]. To address the issue of within-crash correlations and quantify uncertainty in the data, the authors in [26, 41] employed Bayesian models to analyze data and identify factors contributing to motorcycle crashes. The MNL model, on the other hand, is prone to violating the independence of irrelevant alternatives (IIA) criterion (the standard multinomial logit model, which assumes that the error terms (ϵ_{ij}) are independently distributed among alternate outcomes) [16]. The authors [9] estimated a nested logit (NL) model and heterogeneous choice models to overcome these restrictions. Also, the authors in [42] stated that the NL model is not as flexible as heterogeneous models such as the RPL model and that the NL model is more sensitive to the problem of data underreporting.

In addition to the models discussed earlier, other less commonly utilized nonheterogeneity models exist, including ordered probit [43, 44], binary logit [45], and data mining techniques [46–48]. These models offer alternative approaches to analyze and interpret data related to motorcyclist crashes, with each having its own advantages and limitations. For instance, ordered probit models can account for the ordinal nature of injury severity outcomes, while binary logit models are useful when predicting the probability of a crash resulting in an injury or noninjury. Data mining techniques can also be employed to identify patterns and associations within large crash datasets. As such, researchers may consider these alternative models when exploring the complexity of motorcyclist crash-related data.

Random parameters models, also known as random effects models, are a useful tool for modeling unobserved heterogeneity in crash data. Unlike fixed models that assume constant parameter estimates across all observations, RPL models allow for variation in the effects of parameters across different observations. As a result, RPL models have been found to have better model fit and more accurate predictions than fixed models. For example, the full Bayesian random parameters logistic regression approach [49] and the random parameters multivariate Tobit model [41] have both outperformed fixed models. Another advantage of heterogeneity models like RPL models is that they are not affected by the independence of irrelevant alternatives problem, which can be a significant issue in fixed models such as the MNL model [50]. This problem arises when adding an irrelevant alternative to a choice set that affects the probability of choosing one of the other alternatives. In the context of crash data, this could occur if a crash's outcome depends not only on the characteristics of the crash but also on the presence of other nearby crashes. Since RPL models allow for individual-specific variations in parameters, they can account for such unobserved heterogeneity and provide more accurate estimates of the effects of different factors on crash outcomes. Other models have also been proposed that address the problem of unobserved heterogeneity in common discrete choice models for predicting the severity of crashes [51].

In recent years, heterogeneous studies on crash injury severity analysis of various road users have been employed: RPL (also known as the mixed logit model) [51–55], random parameters ordered probability models [56–58], latent-class

models [14, 51, 59], Markov switching models with random parameters [60], and bivariate/multivariate models with random parameters [61].

However, directly comparing the performance of these models using numerical measures such as the likelihood ratio test is not suitable, as it fails to capture the complexity and subtleties of heterogeneity modeling in this domain. Therefore, researchers typically rely on theoretical insights and empirical evidence to evaluate the effectiveness of different heterogeneity models for crash data analysis. Further, latent class models and Markov switching models are limited in their ability to extend beyond classes. In addition, when comparing RPL with latent class models, latent class models will eventually require a probability model such as MNL or even RPL to determine their probability [30]. Based on [51], the RPL model prediction of probabilities for all three levels of injury severity was more fit to the data (on average) than the latent class model prediction of probabilities. Eventually, our choice between heterogeneity models was RPL or mixed logit models. Also, the RPL method has been employed more than others in prior research to address the problem of unobserved heterogeneity in the severity of crashes among different road users [30, 51].

The severity of the crashes was divided into 3 categories: minor injury (bruising, contusions, unconsciousness, discomfort, or complaints of pain soreness), serious injury (i.e., hospitalization), and fatal injury (i.e., killed in crash place or death within 30 days after crash). The authors in [62] pointed out around 30 years ago that not all traffic crashes were reportable and that not all reportable crashes were really recorded. Property damage only (PDO) crashes are more likely to be unreported (according to [63], about half of them are likely to be unreported). As they constitute a small proportion of the data, they were not chosen to give a severity level.

RPL is an advanced statistical model that builds upon MNL, a traditional modeling technique. RPL offers the advantage of incorporating a distribution function for the coefficients that describe the impact of unobserved factors. This means that RPL can provide a more nuanced and unbiased analysis than MNL. In contrast, MNL is limited in that its β coefficients always have constant values, and it cannot address heterogeneous effects. Therefore, RPL is an ideal approach for researchers and analysts who need to account for the complex interplay of various factors and their effects on outcomes. By using RPL, they can gain a more accurate understanding of the underlying patterns and make informed decisions based on the insights gained from their analyses.

The RPL model utilized in this research is shown as follows.

The severity function indicates that each individual crash i reflects injury severity j as follows:

$$U_{ij} = \beta_j X_{ij} + \varepsilon_{ij}. \quad (1)$$

The approach proposed in [64] is used to calculate the probability of a crash i resulting in driver injury severity j given as follows:

$$P_i(j) = \frac{\text{EXP}(\beta_j X_{ij})}{\sum_j \text{EXP}(\beta_j X_{ij})}. \quad (2)$$

By allowing β_j to vary across observed crash dataset features, the RPL model formulation addresses the unobserved heterogeneity issue. The outcome constants and β_j parts can be fixed or randomly distributed with fixed means across all parameters. As a result, a mixing distribution is used to calculate crash severity probability [65].

$$P_i(j|\varphi) = \int \frac{\text{EXP}(\beta_j X_{ij})}{\sum_j \text{EXP}(\beta_j X_{ij})} f(\beta_j|\varphi) d\beta_j. \quad (3)$$

Here $P_i(j|\varphi)$ is the probability of injury severity j conditional on $f(\beta_j|\varphi)$ and $f(\beta_j|\varphi)$ is the density function of β_j and φ is a known vector of parameters (mean and variance) that define the density function. X_{ij} is a vector of observable features (such as crash/roadway/environment/driver/vehicle-specific parameters) that influence the injury result j for crash i . RPL probabilities are a weighted average of various values of β_j across crashes, with some components of the vector β_j will be fixed and others being randomly distributed. If the parameters are random, the density function $f(\beta_j|\varphi)$ generates the RPL weights. Normal, log-normal, triangular, and uniform distributions are considered for the functional form of the parameter density functions. There is no mathematical proof that one distribution is better than the other. The statistical fit of the model can be used to make the final choice of the random parameter [12]. The current study examined all four distributions for random parameters, and the normal distribution had a higher log-likelihood than the others. Also, according to past studies, the normal distribution provided the best fit for crash injury severity data [51, 53, 54].

Using the maximum likelihood method and 500 Halton draws [66], the RPL model is calculated in the NLOGIT software. The marginal effects are also computed to make the estimated results easier to comprehend. The marginal effects are the differences in estimated probability when indicator variables are changed from zero to one.

$$E_{X_{ik}}^{P_i(j)} = P_i(j|X_{ik} = 1) - P_i(j|X_{ik} = 0). \quad (4)$$

We reviewed past studies on crash severity heterogeneity to determine the randomness of the parameters. The basis for decision-making was the significance of the standard deviation of each random parameter [67].

3. Data

After preprocessing the motorcycle crash data in the State of Victoria obtained from VicRoads [29], 10,897 data related only to urban nonintersection motorcyclist crashes (not pillion passenger information) from the beginning of 2009 to November 2020 were selected for analysis. Note that VicRoads is a statutory corporation in the State of Victoria, Australia, responsible for driver licencing and vehicle registration and is a part of the Department of Transport, Victoria. VicRoads provides crash statistics to researchers

and other stakeholders to assist with education and research and develop road safety programs and initiatives.

The data were divided into three groups: fatal injury, serious injury, and minor injury. Crashes that occurred in the intersection-affected region, which had previously been analyzed, were then removed. The quantity and percentage of the variables that may impact the crash severity are depicted in Table 1 based on the level of injury suffered by the motorcyclists.

Some important characteristics, such as motorcycle type or engine size, alcohol-impaired riding, licence status, trip purpose, and annual average daily traffic (AADT), which have been demonstrated to influence crash severity in earlier research, were not examined in this analysis. This was due to a database absence or missing data.

The correlation between each characteristic was first determined, and among those with a clear connection, one was kept while the others were eliminated. The analysis was performed using the following features:

3.1. Human Factors

3.1.1. Sex. We categorized it into two groups: male and female after excluding information on motorcyclists with unknown or missing gender data. Although there are clear physiological differences between male and female (justifying the use of an indicator variable like 1 for females and 0 for males), there is also a great variation in the same gender, such as differences in height, weight, bone density, levels of caution, and other factors that researchers are usually unaware of [30]. The impact of rider sex on crash data has been considered a heterogeneous variable, as the effect of the same gender on crash outcomes may vary across different crashes.

3.1.2. Age Group. We divided the age group into three categories, as in previous classifications [40, 68]: under 26 years old, between 26 and 59 years old, and above 59 years old. Age is linked to a person's physical characteristics, as well as their reaction times, risk-taking behavior, and other factors that may impact the severity of an injury. However, because age is only a proxy for these elements (which researchers are unable to see and measure), the impact of age on injury severity may differ among people of the same age, as age is frequently used as an age group indication variable [38]. Considering that, despite the obvious differences between young and old, a middle-aged person might still exhibit youthful capabilities with good nutrition and exercise. Alternatively, a young person may not be energetic because of factors such as sickness or inactivity. It has been tried to be viewed as a heterogeneous variable as a consequence.

3.1.3. Having a Pillion Passenger. Motorcycle crashes with at least one pillion passenger and motorcycle crashes without a pillion passenger have been separated into two categories [21].

3.1.4. Helmet Use. Wearing a helmet has always been an effective way to reduce the severity of motorcycle crashes. When an appropriate protective helmet was used, the usage of the helmet was classified as "Yes"; when the motorcyclist did not wear a helmet, it was categorized as "No."

3.2. Vehicle Factor

3.2.1. Motorcycle's Age. The difference between the date of the crash and the date of manufacturing of the motorcycle was used to calculate the motorcycle age. Based on the previous research on the Victorian motorcycles [69], motorcycles had a median age of 5 years and a mean age of 7 years. In addition, our preprocessed data showed that the mean age of motorcycles was 6.84 years. So, we divided vehicle age into two categories: under 7 years and more than 7 years.

3.3. Temporal Factors

3.3.1. Day of the Week. We divided the days of the week into weekdays and weekends [70]. Even if there are no features specifically relevant to the trip's purpose, the day of the week could be relevant. We consider it as a heterogeneous feature, since there are behavioral differences between recreational riding and commuting or working purposes.

3.3.2. Time of the Day. Based on earlier research [68], we classified the time period of the crash into five groups based on the volume of traffic: early morning or midnight hours (00:00–6:29 A.M), morning peak hours (6:30–8:59 A.M), day off-peak hours (9:00 A.M–14:59 P.M), evening peak hours (15:00–18:29 P.M), and night off-peak hours (18:30–23:59 P.M).

3.4. Environmental and Roadway Factors

3.4.1. Light Condition. We classified light conditions into three categories based on the amount of lightness available [71]: 1-light (daytime or nighttime with sufficient light in the crash area) 2-dark (a nighttime crash at a location with insufficient lighting or when the lights were turned off at the time of the crash) and 3-dusk/dawn. Because the time of day was classified based on traffic volume, there was no high (5.66%) correlation between the time of day and light conditions.

3.4.2. Road Surface Condition. We divided road surface conditions into two categories: normal (dry) and slippery (wet/snowy/icy/muddy) [72, 73].

3.4.3. Road Surface Type. We considered the road surface type as paved and unpaved (including gravel roads) surfaces [68].

3.5. Crash Factors

3.5.1. Speed Limit Zones. The authors in [69] reported that Victorian motorcycle riders are more likely than drivers of all other types of vehicles to exceed the legal speed limit, particularly in areas where the speed limit is greater than

TABLE 1: Descriptive statistics of independent factors.

Variables	Fatal injury	Serious injury	Minor injury	Total
<i>Sex</i>				
Male	322 (3.22%)	4734 (47.37%)	4936 (49.39%)	9992 (91.69%)
Female	14 (1.54%)	387 (42.76%)	504 (55.69%)	905 (8.30%)
<i>Age group</i>				
<26 years old	62 (2.21%)	1247 (44.48%)	1494 (53.30%)	2803 (25.72%)
26–59 years old	237 (3.23%)	3454 (47.17%)	3631 (49.59%)	7322 (67.19%)
>59 years old	37 (4.79%)	420 (54.40%)	315 (40.80%)	772 (7.08%)
<i>Helmet use</i>				
Yes	312 (2.98%)	4877 (46.63%)	5269 (50.38%)	10458 (95.97%)
No	24 (5.46%)	244 (55.58%)	171 (38.95%)	439 (4.02%)
<i>Speed limit zones</i>				
≤ 50 km/h	39 (1.83%)	864 (40.56%)	1227 (57.60%)	2130 (19.54%)
> 50 km/h	297 (3.38%)	4257 (48.55%)	4213 (48.05%)	8767 (80.45%)
<i>Motorcycle's age</i>				
≤ 7 years old	173 (2.56%)	3112 (46.06%)	3471 (51.37%)	4141 (61.99%)
> 7 years old	163 (3.93%)	2009 (48.51%)	1969 (47.54%)	6756 (38.00%)
<i>Day of the week</i>				
Weekdays	175 (2.63%)	3014 (45.30%)	3464 (52.06%)	6653 (61.05%)
Weekends	161 (3.79%)	2107 (49.64%)	1976 (46.55%)	4244 (38.94%)
<i>Time of day</i>				
00:00–6:29 A.M	34 (7.02%)	223 (46.07%)	227 (46.90%)	484 (4.44%)
6:30–8:59 A.M	24 (2.42%)	407 (41.11%)	559 (56.46%)	990 (9.08%)
9:00 A.M–14:59 P.M	154 (3.14%)	2278 (46.55%)	2461 (50.29%)	4893 (44.90%)
15:00–18:29 P.M	82 (2.40%)	1638 (48.10%)	1685 (49.48%)	3405 (31.24%)
18:30–23:59 P.M	42 (3.73%)	575 (51.11%)	508 (45.15%)	1125 (10.32%)
<i>Having a pillion passenger</i>				
Yes	30 (5.85%)	267 (52.14%)	215 (41.99%)	512 (4.69%)
No	306 (2.94%)	4854 (46.74%)	5225 (50.31%)	10358 (95.31%)
<i>Light condition</i>				
Light	291 (3.03%)	4468 (46.65%)	4818 (50.30%)	9577 (87.88%)
Dark	28 (5.87%)	250 (52.41%)	199 (41.71%)	477 (4.37%)
Dusk/dawn	17 (2.01%)	403 (47.80%)	423 (50.17%)	843 (7.73%)
<i>Road surface condition</i>				
Dry	315 (3.41%)	4447 (48.26%)	4451 (48.31%)	9213 (84.54%)
Slippery	21 (1.24%)	674 (40.02%)	989 (58.72%)	1684 (15.45%)
<i>Road surface type</i>				
Paved	319 (3.45%)	4365 (47.21%)	4561 (49.33%)	9245 (84.83%)
Unpaved	17 (1.02%)	756 (45.76%)	897 (53.20%)	1652 (15.16%)
<i>Number of vehicles</i>				
Single-vehicle crash	118 (1.95%)	2884 (47.82%)	3028 (50.21%)	6030 (55.33%)
Multivehicle crash	218 (4.47%)	2237 (45.96%)	2412 (49.55%)	4867 (44.66%)

The bold values specifically represent the total percentages that have been appropriately mentioned in the third line of the results and discussion section.

50 km/h. We divided speed limits into two categories: up to 50 km/h (including 50 km/h) and above 50 km/h, as other Victorian crash severity studies suggested [68, 74].

3.5.2. Number of Vehicles. This variable is classified into two types based on the number of vehicles involved: single-vehicle crashes and multiple-vehicle crashes [23].

4. Results and Discussion

Logistic regression typically chooses the reference category for features and severities based on the quantity of each category and prefers it to be the normative category. Therefore, the most frequent value in each variable (whose

total percentages are bolded in Table 1) was chosen as the reference. The estimation results of the RPL model for motorcycle crashes on urban nonintersection Victorian roadways are shown in Table 2. The calculated coefficients, chi-square, log-likelihood, McFadden *R*-squared, marginal effects, and *p* values are shown in this table. For each injury level, the variable's coefficient was calculated using the maximum likelihood method. As indicated in the table, the final model's outcome shows a better statistical fit than the initial testing models (log-likelihood = −7632.736, chi-squared = 6034.515, McFadden pseudo-*R*-squared = 0.378). According to [75], McFadden's pseudo-*R*-squared value between 0.2 and 0.4 indicates an excellent fit. The marginal effects in the mentioned categories show the

TABLE 2: The RPL model's output for motorcycle crashes on urban nonintersection roadways in Victoria.

Variable	Coefficient	Standard error	p value	Fatal injury (FI)	Serious injury (SI)	Minor injury (MI)
<i>Fatal injury (FI)</i>						
Constant	4.288***	0.61706	<0.001			
Slippery road	-2.794***	0.39521	<0.001	-33.64	31.62	2.02
No helmet use	1.802**	0.53450	0.031	32.94	31.37	1.56
Female rider	-1.019***	0.27028	<0.001	-21.37	13.07	8.30
Standard deviation for "female rider" (normally distributed)	1.410**	0.57571	0.0143			
Weekend trip	3.617***	1.14493	<0.001	10.34	-6.98	-3.36
Standard deviation for "weekend trip" (Normally distributed)	4.297***	1.04271	<0.001			
Unpaved road	-0.493**	0.20910	0.0183	-6.27	4.74	1.52
Dark light condition	1.314***	0.32611	<0.001	10.55	-5.02	-5.52
Dusk/dawn light condition	0.644**	0.26263	0.0141	3.52	-1.74	-1.77
Rider's age above 59 years (old rider)	2.517***	0.23892	<0.001	7.35	-5.68	-1.66
Standard deviation for "old rider" (normally distributed)	1.485*	0.86342	0.0854			
Early morning or midnight hours (00:00–6:29 A.M)	0.269**	0.13328	0.0430	12.03	-0.88	-11.15
<i>Serious injury (SI)</i>						
Constant	1.147***	0.32622	<0.001			
Pillion passenger presence	1.230***	0.29835	<0.001	-6.25	14.20	-4.95
Motorcycle's age above 7 years	1.214**	0.71447	0.0291	-4.14	13.85	-9.71
Speed limit above 50 km/h	2.183***	0.46550	<0.001	-3.82	4.14	-0.32
Morning peak hours (6:30–8:59 A.M)	0.299**	0.15088	0.0471	-3.55	3.86	-0.30
Rider's age under 26 years (young rider)	-0.504***	0.18809	0.0078	2.16	-2.27	0.10
Standard deviation for "young rider" (normally distributed)	0.85865*	0.46907	0.0672			

***, **, and * ⇒ significance at 1%, 5%, and 10% level. RPL model statistics: log-likelihood function = -7632.73696, McFadden pseudo-*R*-squared = 0.37899, Chi-squared = 6034.51582. The bold values of the marginal effects at a specific level of severity indicate their significance solely at that particular level.

impact of switching from the reference category (normal and maximum) to the mentioned category at each injury level. For example, the fatal injury marginal effect of the female rider indicator = -21.37% means if the rider's sex switches from male to female, the probability of a fatal injury reduces by 21.37%.

The estimation findings reveal that the following factors increase the probability of a fatal injury: not wearing a helmet, old riders (more than 59 years old), riding during early or midnight hours (00:00–6:29 A.M), weekend motorcycle use, and insufficient lighting (dark and dusk/dawn). And having a pillion passenger, a motorcycle age of more than 7 years, riding at higher speed limits (more than 50 km/h) or during peak hours in the morning (6:30–8:59 A.M), and being in the younger age group (less than 26 years old), increase the probability of a serious injury. Our conclusions are based on the features that are present in the dataset. The other important factors like motorcyclist experience or licence status were not available in the dataset. As such, we recommend considering these factors (if known) in future studies.

4.1. Random Variables. According to the RPL model results and the significance of standard deviations, the following variables were chosen as heterogeneous variables.

4.1.1. Sex. According to the RPL model's coefficients and p values (Table 2), the female rider indicator is significant in fatal injury. Table 2 also shows the marginal effects of the female rider indicator. Based on the results of the marginal effects, female motorcyclists had a lower risk of fatal injury (fatal injury marginal effect = -21.37%). In previous studies, it has been found that male motorcyclists are more likely to die or have serious injuries in motorcycle crashes [24, 76]. These results may originate from male motorcyclists being more likely to ride at faster speeds, engage in unsafe driving behaviors, and disregard traffic laws [77]. However, contrary to the aforementioned findings, [78] revealed a reduction in the likelihood of severe injury for male riders involved in motorcycle crashes.

4.1.2. Age Group. With a 99% confidence interval, the younger age group (under 26 years old) is significant in serious injury level, and the older age group (above 59 years old) is significant in fatal injury level. The results also indicate that motorcyclists above the age of 59 (fatal injury marginal effect = 7.35) are more likely to experience a fatal injury. And motorcyclist under the age of 26 years (serious injury marginal effect = -2.27%) are less likely to be involved in a serious injury crash and, therefore, more likely to experience a fatal or minor injury. Our finding is in line with most past studies that concluded that injury severity in motorcycle crashes increases with increase in the rider's age [15, 17, 18]. According to research conducted by [79], as the body ages, there is a decline in bone density and strength, modifications in the distribution of subcutaneous and visceral fat, and a decrease in the flexibility of the chest wall. These changes can lead to more severe injuries following exposure to trauma. Moreover, the study by [39] highlighted

that age-related alterations in body structure can result in a heightened risk of injury severity for older people.

4.1.3. Day of the Week. Furthermore, when engaged in weekend crashes (Saturday and Sunday), motorcyclists were shown to have a larger risk of fatal injury (fatal injury marginal effect = 10.34%), and it was significant with a p value <0.001. This conclusion is consistent with previous studies [14, 80]. This might be because motorcyclists prefer to take recreational road trips on weekends (because of the holidays) when traffic flow is low; so motorcycle riders may engage in risky behaviors such as drifting, careless riding, and speeding, thereby increasing the likelihood of fatal injuries [81].

4.2. Fixed Variables

4.2.1. Helmet Use. Motorcyclists who do not wear a helmet are 32.94% (fatal injury marginal effect in the not wearing helmet category) more likely to be in fatal crashes. This observation is consistent with earlier research findings, where it has been found that wearing a safety helmet reduces the chance of fatal and incapacitating injuries in motorcycle crashes [18, 82, 83]. Helmet use has been shown to minimize the fatality risk of motorcyclists by 2.12 times [84]. Among the several variables reviewed in this article, not wearing a helmet seems to be the leading cause of the increasing probability of fatality.

4.2.2. Speed Limit Zones. As reported by [69], motorcycles were statistically more likely than other vehicles to exceed the speed limit by more than 10 km/h in speed limit zones of 60, 80, 90, and 100 km/h, but not in speed limit zones of 40 and 50 km/h, in the State of Victoria. According to our research results, speed limit zones above 50 km/h were significant with a 99% confidence interval in the serious injury level, and serious injury probability increased by 4.14% in this category. Our finding is in line with prior research findings that concluded that in motorcycle crashes, riding at higher speed limits causes severe injury levels [14, 15].

4.2.3. Motorcycle Age. According to the RPL model results, the age of the motorcycle indicator appeared to be significant, with at least a 95% confidence interval. Riding on a motorcycle that is more than 7 years old raises the chances of serious injury by 13.85%. This result is similar to [16], which found that newer motorcycles (5 years) are less likely to be involved in serious crashes, and each 1% rise in motorcycle age translates into a 0.6% drop in the probability of a no-injury crash (and thus a higher likelihood of other crash-injury-severity types).

4.2.4. Time of Day. Early morning or midnight hours (00:00–6:29 A.M) and morning peak hours (6:30–8:59 A.M) were statistically significant in different severities, with a 95% confidence interval. Early morning or midnight hours (00:00–6:29 A.M) raised the risk of fatal injury by 12.03. It was also observed that there is a 3.86% increase in the risk of

serious injury during the next time interval (6:30–8:59 A.M.). There is a difference in the outcome of this variable. Based on most previous studies, riding a motorcycle in the early morning hours raises the risk of fatality and incapacitating injuries [21, 24, 25]. The authors in [85] also concluded that off-peak hours increase fatality.

4.2.5. Having a Pillion Passenger. When a motorcycle has a pillion passenger, serious injuries are 14.20% more likely to occur. This finding is consistent with earlier research. The authors in [21] stated that the severity of the injury increases when a pillion passenger is present, but the intensity of the damages reduces. This might be due to the fact that there were at least two persons involved in the event, which increases the probability of the crash being categorized as having a higher severity level. Also the distractions may arise from talking and paying attention to the pillion passenger.

4.2.6. Light Condition. Dark and dusk/dawn indicators were significant in fatal injury severity with 99% and 95% confidence intervals, respectively. In addition, from the result of the marginal effect, it can be concluded that light conditions in the categories of dark (fatal injury marginal effect = 10.55%) and dusk/dawn (fatal injury marginal effect = 3.52%) increase the probability of fatal injury in motorcycle crashes. Even though various findings have been stated in the literature regarding the effect of light conditions, this study's finding is consistent with the majority of them [9, 18, 82].

4.2.7. Road Surface Condition. Slippery road surface conditions were shown to reduce the likelihood of a fatality by 33.64%. This is consistent with past studies [15, 21, 86] findings that wet roadway conditions increase the chance of no injury in motorcycle crashes. Under slippery conditions, although motorcycle riders are more likely to be involved in a crash, they may be riding cautiously or reducing speed so that the injury severity decreases. A study on driving behavior has shown that under rainy conditions, most drivers tend to decrease their speed and drive cautiously [87].

4.2.8. Road Surface Type. The indicator variable “unpaved roads” was found to be significant, with a 95% confidence interval in serious injury. According to the results of the marginal effects, it reduced the risk of a fatal injury by 6.27%. This is consistent with [88], finding that urban motorcycle crashes on unpaved roads were more likely to result in incapacitating injury than fatal injury. Similar to the slippery road condition argument, it is possible that on gravel and unpaved roads, motorcyclists are more careful than normal, resulting in fewer fatalities, yet the road condition causes more serious and minor injury crashes.

5. Conclusion

This study aimed to analyze the factors contributing to motorcycle crash severity on Victorian urban non-intersection roadways while considering the heterogeneity of

parameters. To achieve this aim, 10,897 data on motorcycle crashes that occurred at urban nonintersection in the State of Victoria, Australia, were evaluated using the RPL model from 2009 to November 2020.

Motorcycle crashes were classified as having three levels of severity: minor injuries, serious injuries, and fatal injuries. The risk factors were the motorcyclist's age and gender, speed limit zone, time of day, day of week, helmet use, motorcycle age, presence of a pillion passenger, road surface condition, type of road surface, light condition, and the number of vehicles involved in the crash.

The marginal effect of parameters was calculated to determine the significance of the factors. According to the findings, the following factors enhanced the probability of fatal injury: not wearing a helmet, being in an older age group, riding during early morning or midnight hours, weekend motorcycle use, and insufficient lighting (dark and dusk/dawn). Also, having a pillion passenger, the motorcycle age of more than 7 years, riding at higher speed limits (more than 50 km/h) or during peak hours in the morning (6:30–8:59 A.M.), and being in the younger age group (less than 26 years old) were found to increase the chance of serious injury.

Although the number of motorcyclists who did not wear a helmet was notably lower than the number of those who did, not wearing a helmet appeared to be the most critical cause of increasing fatalities. It shows that educating motorcyclists on the importance of wearing a helmet and applying strict enforcement measures for not wearing a helmet is important to reduce fatalities.

By comparing our findings with those by [23], it can be concluded that older age, unpaved surfaces, riding in the early morning or midnight hours, and weekend motorcycle use are important risk factors for fatal injury in both intersection crashes and nonintersection crashes. However, factors like helmet use and lighting conditions are crucial in nonintersection crashes. These variances in the results may have been due to the present study's analysis of unobserved heterogeneity of data or by variations in rider behaviors between junction and nonintersection situations. For example, intersections are usually in better lighting conditions, even if the lamps are off. Moreover, intersections are generally exposed to conflicting traffic flows, and motorcyclists may be more cautious when approaching them, reducing their speed accordingly. Consequently, if they are involved in any crash at intersections, the severity of head injuries may be less than when they are speeding away from intersections. These variances in the results may have been due to the present study's analysis of unobserved data or by variations in rider behaviors between junction and nonintersection situations. Furthermore, the intersection study found that the number of vehicles involved in crashes was a significant factor in intersection crashes but not in nonintersection crashes, regardless of the severity level of the crash. One possible explanation for this discrepancy is the intersection's characteristics, such as the presence of conflicting traffic flows and therefore a higher possibility of multivehicle crashes. Intersection studies have also reported that other intersection characteristics, such as unpaved

intersections, intersections controlled with stop or give-way signs, and T-intersections, were significant variables for severe injuries in intersection crashes. Intersection variables, however, are not related to nonintersection crashes. Therefore, it seems crucial to consider the different characteristics of intersection and nonintersection crashes and unobserved heterogeneity of crash data when analyzing the factors contributing to crash severity.

The current study was limited by the data available on the Vic-Roads database. New parameters (for example, motorcyclist experience and licence, and intoxicated riders) may aid in investigating more precise and comprehensive studies. One potential avenue for future research would be to consider the AADT and traffic composition, particularly heavy vehicle percentage, as they have been found to significantly impact traffic characteristics and increase the likelihood of severe injury or fatality [89]. The findings from this study may assist Victorian road safety policy managers in picking effective strategies for improving motorcyclists' safety at urban nonintersections. This may include improving the light conditions at nonintersection, encouraging the motorcyclist to maintain motorcycles regularly, and educating the motorcyclist to avoid distractions (e.g., conversation with pillion passengers while riding) and ride responsibly on the weekends (holidays).

Data Availability

Data can be made available by contacting the second co-author, Dr. Kayvan Aghabayk (kayvan.aghabayk@ut.ac.ir).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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