ASSESSMENT OF KEY CONTRIBUTING FACTORS TO MOTORCYCLE CRASH SEVERITY IN DHAKA CITY THROUGH COMPARATIVE MODELING APPROACH

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ABSTRACT

Road accidents pose a significant threat to public safety, with motorcycle-related incidents showing a concerning upward trend in terms of both usage and fatalities. This study aims to explore the factors contributing to motorcycle crash severity by analyzing data from a four-year period (2017-2020), collected from the Accident Research Institute (ARI), BUET. A total of 67 variables has been collected from accident data form and correspondingly 19 variables have been selected for analysis, which are deemed impactful for accident severity; finally, seven variables have been chosen for Multinomial Logit (MNL) model and Ordered Logit (OL) model through literature review, data cleaning and preprocessing. Under the variable 'Road Class', city roads exhibited a significant negative coefficient (MNL: coefficient=-1.593, p=0.006; OL: coefficient=-1.597, p=0.006), suggesting that accidents on urban roads are associated with lower severity compared to highway crashes. Collision type analysis revealed that crashes involving pedestrians had a significant relationship (MNL: coefficient =-1.919, p=0.037; OL: coefficient=-1.890, p=0.039) relative to head-on collisions, as head-on collisions between motorcycles and other vehicles typically involve higher impact velocities and forces. Whereas crashes at cross junctions were significant only in MNL (coefficient=-1.366, p=0.061), indicating reduced odds of fatal outcomes compared to non-junction locations. Model comparisons based on Log Likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) indicated that the Multinomial Logit model outperformed the Ordered Logit model in predicting crash severity. These results provide valuable insights for policy development and targeted interventions aimed at improving motorcycle safety in urban settings of Bangladesh.

Keywords: *Motorcycle Crash Severity, Multinomial Logit Model, Ordered Logit Model*

1. INTRODUCTION

Traffic safety is a major issue that addresses road traffic accidents (RTAs), which have eventually become a major public health and socio-economic concern all over the world, especially in developing countries like Bangladesh. According to the World Health Organization (*WHO, 2018*), more than 1.35 million people die every year due to RTAs, and more suffer from non-fatal injuries, which often lead to disabilities and economic hardship. In developing countries like Bangladesh, increased urbanization and motorization, and inadequate road safety have intensified the problem multifold (Alam et al., 2025). Consequently, the number of RTAs has also gone up, especially in the capital of the country, Dhaka. Dhaka is the most vulnerable both in terms of the total number of accidents and accident rates (Bayes, 2013).

Rapid growth in personal vehicles is considered vastly responsible for the ever-growing accident rate. Among the personal vehicles, motorcycles are one of the most vulnerable vehicle groups because of their size, limited protection, and control mechanisms (López et al., 2025; Miah et al., 2024). Over the last decade, motorcycle use in Dhaka has increased dramatically, primarily due to affordability, growing use in delivery services, and ride-sharing platforms (Zafri et al., 2021). Motorcyclists are frequently exposed to hazardous situations that increase the likelihood of severe crashes. Recent studies showed that motorcycle-dominated crashes account for around 27% of all crashes in Bangladesh (Saha et al., 2025a). Moreover, Bangladesh stood in 2nd position among Asian countries, with around 20 motorcyclist deaths per ten thousand vehicles (Saad et al., 2025). Understanding the causes and contributing factors behind motorcycle accidents is crucial for developing safety and law enforcement strategies and creating transportation policies in Bangladesh. Unfortunately, the underlying causes of these collisions and the required safety measures are still inadequately understood.

Statistics-based models and discrete choice models (DCMs) can play a key role in explaining the severity and reasons of motorcycle accidents, thus helping to improve safety measures and prevent future collisions. Traditional descriptive methods often fail to capture the categorical and ordered nature of accident severity data. This necessitates the application of special econometric discrete choice models capable of handling such data structures. Unfortunately, systematic research on the predictors of crash severity is limited in Bangladesh. Most studies in Bangladesh have focused broadly on descriptive statistics of accidents (Ahmed, 2013.; Paul et al., 2024; Taspia et al., 2024), crash hotspots (M. Alam & Ahsan, 2013; Jamil et al., 2021), or general or health-based road safety issues (Saha et al., 2025b; Sharmin & Sultana, 2022). This gap restricts policymakers from understanding the complex relationship between different factors that affect accident severity in this region.

Over the past few decades, researchers have increasingly turned to advanced statistical modeling to understand the complex relationships between contributing factors and the severity of road accidents. Many discrete choice models (DCM) are applied for the analysis of crash severity, including multinomial logit model (MNL)(Chen & Fan, 2019; Malyshkina & Mannering, 2008; Shankar & Mannering, 1996), ordered logit model (OL) (Asare & Mensah, 2020; Ortelli et al., 2025; Rezapour et al., 2019), ordered probit model(Abdel-Aty, 2003; Xie et al., 2009), and nested logit model (Patil et al., 2012). There has also been much research where multiple models were implemented to find out the best performing models, which show better accuracy than others. For example, Yasmin et al. (2014) provided a comprehensive empirical comparison of MNL, OL, NL, and mixed logit models to analyze driver injury severity using crash data from the United States. Ye & Lord (2014) compared multinomial logit, ordered probit, and mixed logit models and reported that mixed logit models often handle unobserved heterogeneity better, ordered probit requires smaller samples, and MNL is versatile for nominal categories. There are very few and emerging studies using DCMs in Bangladesh; some notable studies might include modeling the severity (Hasanat-E-Rabbi et al., 2023; Pervaz et al., 2024; Siddique, 2018) and frequency (Hadiuzzaman et al., 2016; Sadeek & Rifaat, 2020; Shaik & Hossain, 2020) of accidents. However, studies on comparison of DCMs for safety analysis of motorcycles in urban structures are more scarce. Considering the above scenario, the objectives of this study are to implement multinomial logit model (MNL) and ordered logit model (OL) for analysis of motorcycle-based accident severity to find the significant responsible factors and to compare the models for better interpretation of the results.

2. METHODOLOGY

The data for this study were obtained from the Accident Research Institute (ARI), Bangladesh University of Engineering and Technology (BUET). ARI collects accident data using its Accident Report Form (ARF). This form contains data on the geometric, environmental, and spatial conditions during accident, as well as vehicle and victim characteristics relevant to accidents. The forms are then processed via Micro-computer Accident Analysis Package five (MAAP5) software for data storage and analysis purposes.

After collecting the data, they were processed through cross-tabulation using Microsoft Excel. For this study, the dataset contained 203 accident events involving motorcycles that occurred during 2017-2020 in Dhaka metropolitan area. The original ARF contained 67 variables but due to blank and improperly filled variables, and to overcome the small sample problem and improve model performance, a recategorization process was carried out where a total of 19 independent variables were selected. Finally after reviewing previous relevant literature, seven independent variables were chosen for analysis. The model development and further work were performed in Python environment.

2.1 Crash Severity Type

The First Information Report (FIR) published by Bangladesh Police categorizes accidents into four levels of severity. An accident that results in the death of any person (or individuals) involved in the accident within 30 days of the accident's occurrence is referred to as a fatal accident. A grievous accident injures the victims and forces them to seek treatment in a hospital, but does not result in any fatalities or other consequences. A simple injury accident involves just minor injuries that may be treated at home and does not necessitate the need for hospitalization. Motor collision represents the damage done to the vehicles or other personal property as a result of the collision. But the lack of events in the simple accident and motor vehicle categories resulted in combining grievous, simple, and motor collisions into the non-fatal accident category. Table 1 shows the distribution of motorcycle accidents in Dhaka metropolitan area based on the above severity classes over the years 2017-2020.

Table 1: Distribution of Motorcycle Accidents in Dhaka Metropolitan Area in 2017-2020 (Accident Severity Class-wise)

Year	Accident Severity Class				Total
	Fatal	Grievous	Simple	Motor Collision	
2017	20	10	2	0	32
2018	42	13	1	1	57
2019	45	23	3	0	71
2020	28	13	2	0	43
Total	135	59	8	1	203

2.2 Multinomial Logit Model

MNL model is suitable when accident severity is treated as a nominal variable with multiple non-ordinal categories. It estimates the probability of each outcome relative to a baseline category, allowing for identifying factors that increase or decrease the likelihood of each severity level separately (Abdulhafedh, 2017). The MNL model's flexibility for handling nominal (non-ordered) categories facilitates detailed interpretation of the influence of individual factors on each severity class. A limitation is that MNL requires more parameters to estimate, which can be challenging especially with smaller datasets. In MNL, one category is taken as the baseline, and the odds of other categories are modeled relative to this baseline.

The Multinomial Logit model is appropriate when the dependent variable is categorical with more than two nominal (non-ordered) categories. Let the dependent accident severity variable y have J possible outcomes $\{1,2,\ldots,J\}$ where each corresponds to a severity level (e.g., motor collision, simple injury, grievous injury, fatal). The probability that observation i belongs to a category j is modeled as:

$$P(Y_i = j) = \frac{\exp(Z_{ij})}{\sum_{k=1}^{J} \exp(Z_{ik})} \text{ for } j = 1,2,\ldots,J$$

Where,
$$Z_{ij} = \beta_{j0} + \sum_{m=1}^{K} \beta_{jm} X_{im}$$

Here, X_{im} are the explanatory variables for observation i, β_{jm} are parameters to be estimated, and one outcome category (usually J) is set as the baseline with $Z_{iJ} = 0$ for identification. The model estimates $J-1$ equations modeling the log-odds of each category relative to the baseline:

$$\ln\left(\frac{P(Y_i = j)}{P(Y_i = J)}\right) = \beta_{j0} + \sum_{m=1}^{K} \beta_{jm} X_{im}$$

which allows flexible and separate influences of variables on each severity level. The parameters are estimated using Maximum Likelihood Estimation (MLE).

2.3 Ordered Logit Model

In contrast, the ordered logit model explicitly incorporates the natural ordering of accident severity, recognizing the progression from less severe to more severe outcomes. This model is best suited when severity levels are ranked, but the distances between levels are not necessarily equal. By imposing this ordinal structure, the ordered logit model enhances interpretability and efficiency by exploiting the inherent ordering in the dependent variable. With its fair share of benefits, a drawback might be that ordered logit model imposes a proportional odds (parallel lines) assumption, which can lead to inconsistent parameter estimation if not valid for the data (Eluru & Yasmin, 2015).

The Ordered Logit model is used when the dependent variable y is ordinal, representing an inherent ordering of severity levels (e.g., from least to most severe). The model introduces an unobserved latent variable y_i^*:

$$y_i^* = \beta_0 + \sum_{m=1}^{K} \beta_m X_{im} + \epsilon_i$$

where ϵ_i is assumed to follow the logistic distribution.

The observed categorical outcome y_i relates to y_i^* through a set of increasing thresholds μ_j such that:

$y_i = j \text{ if } \mu_{j-1} < y_i^* \le \mu_j \text{ for } j = 1,\ldots,J$ with $\mu_0 = -\infty$ and $\mu_J = +\infty$.

The cumulative probabilities are modeled as:

$$P(Y_i \le j) = \frac{1}{1 + \exp[-(\mu_j - \beta_0 - \sum_{m=1}^{K} \beta_m X_{im})]}$$

The probability of observing a category j is:

$$P(Y_i = j) = P(Y_i \le j) - P(Y_i \le j-1)$$

2.4 Model Estimation and Evaluation

Both the Multinomial Logit (MNL) and Ordered Logit (OL) models were estimated using the same dataset to facilitate a direct comparison of their performance. To evaluate how well each model fits the data while considering model complexity, several statistical criteria were calculated.

The Akaike Information Criterion (AIC) is computed as:

$$\mathrm{AIC} = 2k - 2\ln(\hat{L})$$

where k is the number of estimated parameters and $\hat{L}$ is the maximized likelihood of the model. Similarly, the Bayesian Information Criterion (BIC) is given by:

$$\mathrm{BIC} = \ln(n) \times k - 2\ln(\hat{L})$$

where n is the sample size. Lower AIC and BIC values indicate a better balance between goodness-of-fit and parsimony. In addition to these metrics, pseudo-R^2 measures such as McFadden's, Cox-Snell's, and Nagelkerke's were used to assess each model's explanatory power relative to a null model.

The statistical significance of each parameter estimate was determined using z-values and corresponding p-values. Due to the relatively small sample size in this study, a 90% confidence level was adopted for assessing significance.

3. RESULTS

The dataset comprised 203 motorcycle accidents that occurred in Dhaka Metropolitan Area during 2017-2020. For multinomial logit model and ordered logit model, the data collected from ARI has been used that originally contained a total of 67 variables. Due to blank and improperly filled variables, and to overcome the small sample problem and improve model performance, a recategorization process was carried out where a total of 19 independent variables were selected. Excluding the variables related to pedestrians and passengers' information, 7 variables have been selected finally for Model analysis.

Table 2: Descriptive Statistics (Total Motorcycle Accident Events =203)

Variable Name	Categories	Frequency	percentage
Junction	None	101	49.8%
	Cross Junction	41	20.2%
	T Junction	38	18.7%
	Others	23	11.3%
Road Class	Highway	63	31.0%
	Regional	18	8.9%
	Feeder	10	4.9%
	City Road	105	51.7%
	Others	7	3.4%
Collision Type	Head On	97	47.8%
	Rear End	26	12.8%
	Side Swipe	22	10.8%
	Hit Parked Vehicle	9	4.4%
	Hit Pedestrian	41	20.2%
	Others	8	3.9%
Vehicle Maneuver	Right Turn	31	15.3%
	Crossing Road	23	11.3%
	Overtaking	48	23.6%
	Going Ahead	83	40.9%
	Others	18	8.9%
Driver Age	<18	20	9.9%
	(18-30)	92	45.3%
	(31-40)	61	30.0%

	>40	30	14.8%
Driver Injury	Simple	39	19.2%
	Fatal	81	39.9%
	Grievous	73	36.0%
	No Injury	10	4.9%
Time	(07.00-11.00)	80	39.4%
	(11.00-16.00)	41	20.2%
	(16.00-21.00)	47	23.2%
	(21.00-07.00)	35	17.2%

Table 2 presents the descriptive statistics of the selected variables used in the analysis. The distribution reveals several notable patterns in motorcycle crash characteristics. Nearly half of the accidents (49.8%) occurred at non-junction locations; in other words, links or carriageways, followed by cross junctions and T-junctions that accounted for 20.2% and 18.7% of crashes, respectively. City roads dominated the crash locations (51.7%), followed by highways (31.0%), indicating that urban street environments present significant challenges for motorcycle safety. Regarding collision patterns, head-on collisions were the most prevalent type (47.8%), followed by hitting pedestrians (20.2%) and rear-end collisions (12.8%). The vehicle maneuver analysis showed that most crashes occurred while motorcyclists were going ahead (40.9%) or overtaking (23.6%), suggesting that these routine riding activities carry substantial risk exposure.

The driver age distribution indicated that young riders aged 18-30 years constituted the largest group (45.3%), followed by those aged 31-40 years (30.0%). Driver injury severity statistics revealed a concerning pattern: fatal injuries represented 39.9% of cases, followed by grievous injuries consisting of 36.0% occasions, collectively demonstrating the severe consequences of motorcycle accidents in the study area. Temporal analysis showed that crashes were most frequent during morning hours (07:00-11:00) at 39.4%, followed by evening hours (16:00-21:00) at 23.2%, corresponding to peak commuting periods.

3.1 Multinomial Logit Model

Table 3 summarizes the results of the multinomial logit model (MNL) estimation. As simple and motor collision type accidents are scarce, a separate dependent variable was created that included grievous, simple and motor collision and was named as non-fatal accidents, which was also eventually selected as the base.

Table 3: Results and Performance of Multinomial Logit Model

	Category	**Coefficient**	**z-value**	**p-value**
Constant		4.276	2.395	0.017
Junction (None)	Cross Junction	-1.366	-1.872	**0.061**
	T Junction	-0.197	-0.209	0.834
	Others	-0.646	-1.018	0.309
Road Class (Highway)	Regional	-2.014	-1.615	0.106
	Feeder	-0.078	-0.072	0.943
	City Road	-1.593	-2.734	**0.006**
Collision Type (Head On)	Rear End	-0.156	-0.19	0.849
	Side Swipe	-1.113	-1.18	0.238
	Hit Parked Vehicle	-2.124	-1.298	0.194
	Hit Pedestrian	-1.919	-2.087	**0.037**
Vehicle Maneuver (Right Turn)	Crossing Road	-0.449	-0.289	0.773
	Overtaking	-2.305	-1.962	**0.050**
	Going Ahead	-0.517	-0.591	0.554

	Others	-0.851	-0.794	0.427
Driver Age (>40)	<18	1.377	1.104	0.270
	(18-30)	-0.092	-0.136	0.892
	(31-40)	0.946	1.236	0.216
Driver Injury (Simple)	Fatal	0.459	0.754	0.451
	Grievous	-3.97	-5.396	**0.000**
Time (11.00-16.00)	(07.00-11.00)	-0.975	-1.408	0.159
	(16.00-21.00)	-0.588	-0.798	0.425
	(21.00-07.00)	0.072	0.085	0.932
Log-Likelihood		-71.981		
AIC		189.962		
BIC		265.1227		
McFadden R^2		0.396		

With 90% significance level, the variables having a p-value less than 0.1 appear to be significant for accident severity and impactful on its criteria. Cross junction from Junction type, City-road from Road class, Hit pedestrian from Collision type, Overtaking from vehicle maneuver, Grievous injury of Driver Injury are the significant factors that affect the propensity of fatal accidents over non-fatal ones according to MNL.

The MNL model estimation results are presented in Table 3. The model achieved a log-likelihood value of -71.981, with an AIC of 189.96 and BIC of 265.12, indicating reasonable model fit given the sample size constraints. The McFadden pseudo-R^2 value of 0.396 suggests that the model explains approximately 40% of the variance in crash severity outcomes, which is considered satisfactory for crash severity modeling applications.

3.2 Ordered Logit Model

The Ordered Logit (OL) model results are summarized in Table 2. Previously mentioned dependent variable, non-fatal accident was categorized as 1, and consequently, fatal accidents were categorized as 2. The model maintains similar coefficient directions, indicating strong consistency with the MNL findings.

Table 4: Results and Performance of Ordered Logit Model (OL)

Variable (Base)	Category	Coefficient	z-value	p-value
Constant		-4.394	-2.395	0.017
Junction (None)	Others	-0.7676	-1.3548	0.1755
	T Junction	0.3897	0.458	0.6469
	Cross Junction	0.5014	0.7545	0.4506
Road Class (Highway)	Regional	-2.0056	-1.6198	0.1053
	Feeder	-0.0304	-0.0283	0.9774
	City Road	-1.5966	-2.7334	**0.0063**
Collision Type (Head On)	Rear End	-0.1411	-0.1715	0.8638
	Side Swipe	-1.0925	-1.1574	0.2471
	Hit Parked Vehicle	-2.003	-1.2428	0.2139
	Hit Pedestrian	-1.8899	-2.0603	**0.0394**
Vehicle Maneuver (Right Turn)	Crossing Road	-0.4391	-0.282	0.778
	Overtaking	-2.3242	-1.9758	**0.0482**
	Going Ahead	-0.5154	-0.5875	0.5569

	Others	-0.8392	-0.7798	0.4355
Driver Age (>40)	<18	-1.4482	-1.3028	0.1926
	(18-30)	-0.4147	-0.3657	0.7146
	(31-40)	-1.3614	-1.1058	0.2688
Driver Injury (Simple)	Fatal	-0.4793	-0.7925	0.4281
	Grievous	-4.4386	-6.3667	**0**
Time(11.00-16.00)	(07.00-11.00)	0.9501	1.3724	0.1701
	(16.00-21.00)	0.3611	0.626	0.5313
	(21.00-07.00)	1.0206	1.4401	0.1498
Log-Likelihood		-72.1523		
AIC		190.3046		
BIC		265.4654		
McFadden R²		0.3946		

At the 90% confidence level, for OL model, city road from Road class, Hit pedestrian from collision type, overtaking from vehicle maneuver, Grievous accident from Driver injury are the significant factors that affect the probability of fatal accidents over non-fatal ones.

The OL model results, summarized in Table 4, demonstrate good consistency with the MNL findings while exploiting the inherent ordering of severity categories. The model achieved a log-likelihood of -72.15, AIC of 190.30, and BIC of 265.47, with McFadden's R^2 of 0.3946. These values are nearly identical to those of the MNL model, suggesting comparable overall fit despite the different modeling approaches.

3.3 Model Comparison

Table 5 presents a comprehensive comparison of model performance metrics. The MNL model demonstrated marginally superior fit with lower log-likelihood, AIC, and BIC (-71.981, 189.962 and 265.1227) values, compared to OL model (-72.1523, 190.3046 and 265.4654); though the differences are minimal. The likelihood ratio chi-square statistics (94.39 for MNL vs. 94.05 for OL) were highly significant ($p<0.001$) for both models, confirming that each model substantially improves upon a null baseline. But to be absolutely specific, the MNL model was superior because of lower log-likelihood, AIC, and BIC values. Better McFadden R^2, Cox-Snell R^2, and Nagelkerke R^2 for MNL compared to OL further corroborate the superiority. Overall, marginally superiority of MNL in fit statistics suggests that imposing ordinal structure on severity classes may be removing degrees of freedom but less relevant gains in efficiency.

Table 5: Performance Metrics of MNL and OL Models

Parameters	Multinomial Logit Model	Ordered Logit Model
Log-Likelihood	-71.981	-72.1523
AIC	189.962	190.3046
BIC	265.1227	265.4654
McFadden R²	0.396	0.3946
Cox-Snell R²	0.3853	0.3842
Nagelkerke R²	0.5447	0.5432
LR Chi²	94.3934	94.0507
p-value	<0.001	<0.001

4. DISCUSSIONS

At the 90% confidence level, several variables emerged as statistically significant predictors of accident severity. Among junction types, crashes at cross junctions showed a significant negative coefficient (MNL: coefficient=-1.366, p=0.061), indicating reduced odds of fatal outcomes compared to non-junction locations. This finding aligns with expectations, as junction areas typically feature lower speeds and heightened driver awareness due to traffic control measures. This is also supported by Haque (Haque et al., n.d.) and Quddus (Quddus et al., 2002). However, in the OL model, this relationship lost statistical significance.

Road class demonstrated substantial influence on crash severity. City roads exhibited a significant negative coefficient (MNL: coefficient=-1.593, p=0.006; OL: coefficient=-1.597, p=0.006), suggesting that accidents on urban roads are associated with lower severity compared to highway crashes. This result is consistent with transportation safety literature (Pervaz et al., 2024; Stiles et al., 2023), where high-speed facilities consistently demonstrate elevated crash severity due to greater impact forces and reduced reaction times. Regional roads also showed a negative tendency (MNL: coefficient=-2.014, p=0.106; OL: coefficient=-2.006, p=0.105), though with slightly reduced statistical significance (Pervaz et al., 2024).

Collision type analysis revealed that crashes involving pedestrians had a significant negative coefficient (MNL: coefficient =-1.919, p=0.037; OL: coefficient=-1.890, p=0.039) relative to head-on collisions. While this may initially appear counterintuitive, it reflects that head-on collisions between motorcycles and other vehicles typically involve higher impact velocities and forces than motorcycle-pedestrian interactions, resulting in more severe motorcyclist injuries (Aung & Tun, n.d.; George et al., 2017; Tavakoli Kashani et al., 2016). This interpretation is supported by biomechanical principles governing crash dynamics.

Vehicle maneuver patterns significantly influenced severity outcomes. Overtaking maneuvers showed a strong negative coefficient (MNL: coefficient=-2.305, p=0.050; OL: coefficient=-2.324, p=0.048), indicating lower severity compared to right-turn maneuvers (reference category). Right-turn conflicts at intersections may expose motorcyclists to angular collisions with crossing vehicles, whereas overtaking crashes, though frequent, may result in lower impact in urban regions with less severity when they occur on straighter road segments. Riders attempting to overtake have sufficient sight distance and are riding at moderate speeds, while right turn maneuver concentrates on intersection conflicts, where several other factors are also involved.

Grievous driver injuries exhibited a highly significant negative coefficient (MNL: coefficient=-3.970, p<0.001; OL: coefficient=-4.439, p<0.001), indicating substantially reduced likelihood of this injury category occurring relative to simple injuries when controlling for other factors. When the injury of driver is grievous, most likely the severity is going to be non-fatal, mostly motorcycles are a single-rider vehicle; when accidents occur, most severely injured persons are drivers of the motorcycles, not passengers or drivers of other vehicles. It also aligns mostly with the fact that motorcycles are one of the most vulnerable groups on the roadway.

An important difference between the models is found in junction variables. While cross junctions showed marginal significance in the MNL, this effect was insignificant in OL (p=0.451). It shows that MNL allows every severity category to have distinct relationships with predictors, whereas OL constrains these relationships to maintain proportional odds across severity levels. While the proportional odds assumption holds, OL provides more efficient estimates; otherwise, MNL offers greater flexibility.

5. LIMITATIONS OF THE STUDY

Under-reporting and inconsistent reporting of crash data is a well-known concern in accident analysis in developing countries (Nilu et al., 2024; Toha et al., 2025). Police-reported crash data contains limitations in documenting severe crashes . Minor motorcycle crashes may not generate police reports, particularly if both parties resolve informally or when riders seek unreported medical treatment. The dataset contains 203 events of motorcycle-involved accidents; the relatively small sample size may constrain the statistical power of the models. Many of the independent variables were excluded due to missing or improperly recorded values. Only a few independent variables were retained for analysis after data cleaning and reclassification. Therefore, many other influential factors might have been omitted.

6. CONCLUSIONS

This study analyzed motorcycle crash severity in Dhaka Metropolitan Area using multinomial logit and ordered logit models on 203 accidents from 2017-2020. The dual-model approach identified consistent and significant associations between several factors and fatal versus non-fatal outcomes.

City roads demonstrated substantial protective effects against fatality compared to highways (MNL: $p=0.006$; OL: $p=0.006$), for moderate speed through urban congestion and traffic control measures. Head-on collisions emerged as the predominant collision type with 47.8% of incidents, showing elevated fatality odds relative to motorcycle-pedestrian collisions. Motorcycle-pedestrian impacts showed reduced motorcyclist fatality risk (MNL: $p=0.037$; OL: $p=0.039$), explained through differential energy dissipation and lower typical impact velocities in urban pedestrian collision contexts. Overtaking maneuvers demonstrated lower fatality odds compared to right-turn baseline ($p \approx 0.050$), as riders attempting to overtake have sufficient sight distance and are riding at moderate speeds, while right-turn maneuver concentrates on intersection conflicts with several other factors involved.

Model comparison revealed marginal superiority of the multinomial logit model (log-likelihood: -71.981 vs. -72.1523; AIC: 189.96 vs. 190.30; BIC: 265.12 vs. 265.47) with both models achieving comparable explanatory power around 40% (McFadden R^2). The consistency of coefficient directions and statistical significance across separate model specifications strengthens confidence in the actual identified relationships, suggesting that the observed patterns represent genuine associations. These results provide valuable insights for policy development and targeted interventions aimed at improving motorcycle safety in urban settings of Bangladesh.

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