A BINARY LOGIT APPROACH TO MODELING ROAD ACCIDENTS IN THE DHAKA METROPOLITAN AREA

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ABSTRACT

Road accidents are a significant public health concern in Bangladesh, with the Dhaka Metropolitan Area (DMA) experiencing a high rate. This study utilizes a binary logit modeling approach to analyze road accident data in the DMA in Bangladesh, aiming to identify key determinants and provide insights for accident prevention. The comprehensive dataset includes 2015–2022 accident records (fatal and non-fatal), road infrastructure data, traffic flow information, and weather conditions. The model estimates the probability of a binary outcome, which is whether an accident occurs or not. Key findings reveal significant factors contributing to road accidents in DMA, including junctions, traffic controls, collision types, weather conditions, road geometry, vehicle type, vehicle fitness, and driver-related factors like age, gender, seatbelt use, and alcohol consumption. The findings can guide policymakers, urban planners, and traffic management authorities in implementing targeted interventions to reduce accident rates and enhance road safety. Strategies such as improved road design, enhanced traffic regulations, and public awareness campaigns could be informed by the results of this study. Addressing the unique challenges of road safety in the DMA is crucial to reducing the human and economic toll of road accidents in the region.

Keywords: *Dhaka Metropolitan Area, Road Accident, Binary Logit Model, Fatal and Non-Fatal Accident, Accident Prevention Strategies*

1. INTRODUCTION

Road traffic fatalities and injuries are a major worry all over the world. According to the World Health Organization, around 1.35 million people die each year as a result of traffic accidents. The injuries sustained in these incidents are considered to be the eighth largest cause of mortality worldwide for all age groups, implying that road traffic accidents currently kill more people than AIDS [1]. The issue is worse in low-income nations. The probability of road traffic mortality is more than three times higher in low-income nations than in high-income ones, where the average incidence is 8.3 fatalities per 100,000 people. Around 57% of these fatalities involved vulnerable road users: pedestrians (37%), cyclists (6%), and motorcyclists (14%).

In Bangladesh, the safety situation is even worse, with a fatality rate per 10,000 motor vehicles of between 60 and 150, compared to just 2 in the USA. Pedestrians account for around 50% of fatalities nationwide and 75% in the capital city of Dhaka [2], [3]. Researchers have identified a number of factors that can influence the severity of pedestrian injuries, including the age and gender of the driver and pedestrian, use of alcohol, time of crash, vehicle types and speed, and adverse weather [4]–[6]. However, these factors may differ in developing countries due to different road, environmental, and traffic characteristics.

Few studies have been conducted on the severity of traffic accident injuries in developing countries using modern statistical approaches. Most research has focused on contributing factors at the roadway level or for the entire country or region. Fewer studies have focused on metropolitan cities, and all of these studies have used the same statistical approaches (i.e., binary logistic, mixed logistic models) [7]–[11]. Research in Bangladesh has mostly focused on the characteristics of pedestrian collisions in Dhaka city or on pedestrian behaviour and perception. There have been no studies examining road accident injury severity in the Dhaka Metropolitan area from 2015 to 2022 using a large-scale data set and the binary logit model.

This study aims to fill existing research gap by analysing road accident data to identify contributing factors, including driver, vehicle, environmental, and built environmental factors. The goal is to determine whether conventional statistical methods can reveal meaningful insights from road traffic crash data, including novel and unexpected findings. This study is unique because it is the first to use a large-scale data set and the binary logit model to examine road accident injury severity in the Dhaka Metropolitan area from 2015 to 2022. The findings of this study may be used to develop sensible policy recommendations for a growing urban society.

2. LITERATURE REVIEW

Road accidents continue to pose a significant threat to public safety worldwide, necessitating a thorough understanding of the factors that contribute to accident severity. This literature review delves into various dimensions of road accidents, exploring the intricate interplay of factors that influence the outcomes of these incidents. The review categorizes these factors into six main domains: traffic and roadway features, environmental aspects, temporal characteristics, vehicular attributes, driver characteristics, and pedestrian characteristics.
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Traffic-related elements, such as higher Average Annual Daily Traffic (AADT) and the percentage of trucks, have been correlated with an increased likelihood of fatalities and severe injuries [12], [13]. Similarly, road geometric features like divided highways, midblock pedestrian crossings, and visual obstructions elevate the risk of injury outcomes [14], [15]. Conversely, flat roads, presence of traffic control devices, and clear weather mitigate the probability of severe injuries. Environmental factors, including rainy weather, dark lighting conditions, and wet road surfaces, heighten the probability of pedestrian injury severity. Land use patterns and night-time significantly influence the outcome of pedestrian accidents, emphasizing the need for tailored interventions based on environmental context [16], [17].

The time of day plays a pivotal role in accident severity. Studies reveal that night-time, especially between midnight and 6 am, is associated with increased fatalities. However, there are variations in findings, with some studies indicating decreased likelihood of fatal injuries during specific daytime hours. Dark, unlighted conditions in the evening and late-night hours also contribute to elevated accident severity [10], [18]. Heavy vehicles have consistently been linked to a higher likelihood of fatalities, whereas lighter vehicles, such as motorcycles and cars, reduce the probability of severe outcomes. Additionally, specific vehicular movements and unsafe vehicle conditions escalate injury severity, highlighting the importance of vehicle safety standards and responsible driving behaviours [19].

Driver-related factors, including age, alcohol consumption, physical condition, and adherence to safety measures, significantly impact accident severity. Young and teenage drivers are prone to higher fatality rates, while older drivers exhibit a decreased probability of severe injuries [14], [20], [21]. Driving under the influence, along with poor physical condition, emerges as a common contributor to fatalities. Safe driving habits, such as seat belt and helmet usage, act as mitigating factors, emphasizing the need for stringent enforcement of traffic regulations [21]. Pedestrians are also susceptible to various risk factors, including distractions like cell phone use [22]. Moreover, pedestrian accidents are influenced by roadway features, lighting conditions, and pedestrian behaviour. Understanding these factors is crucial for designing pedestrian-friendly infrastructure and promoting public awareness about responsible road usage.

Researchers have used various statistical and econometric models to analyse factors contributing to accident severity. The choice of model depends on the nature of the outcome variable. The binary logistic model is used when the outcome is dichotomous, like fatal vs. non-fatal or injury vs. non-injury [11], [23]. Ordered probability models are commonly used when the outcome is ordinal, like minor, moderate, severe, or fatal injury [13]. Unordered models address limitations of ordered models, while generalized ordered logit models relax the proportional odds assumption [19]. Partially proportional odds models allow some variables to violate or follow parallel lines. Most studies on the topic are based on developed countries and use various statistical methods and comparative analysis. However, few studies in developing countries use binary logistic models or multinomial logistic models. In Bangladesh, Sarkar, Tay, and Zafri, Prithul used binary logistic considering [9], [11], [17].

3. MATERIALS AND METHOD

3.1 Study Area

The Dhaka Metropolitan area (DMA), often known as Greater Dhaka, is Bangladesh's capital and the country's biggest metropolitan region (Figure 1). It covers 1,440 square kilometres and has a population of more than 20 million people. The DMA is Bangladesh's economic, political, and cultural centre, housing the government, significant enterprises, and financial institutions. It is also a significant educational and medical colleges, having multiple universities and medical institutions. Despite its fast expansion, the DMA is a lively and energetic city with new buildings and historic mosques. It is a cultural melting pot, with residents from all over Bangladesh and the world. The city is confronted with issues like as traffic congestion, air pollution, and water scarcity. Because of the high population density, there is an immense daily transportation necessity, resulting in significant traffic congestion. To satisfy their everyday travel needs, city residents employ a variety of vehicular and non-vehicular transportation choices.

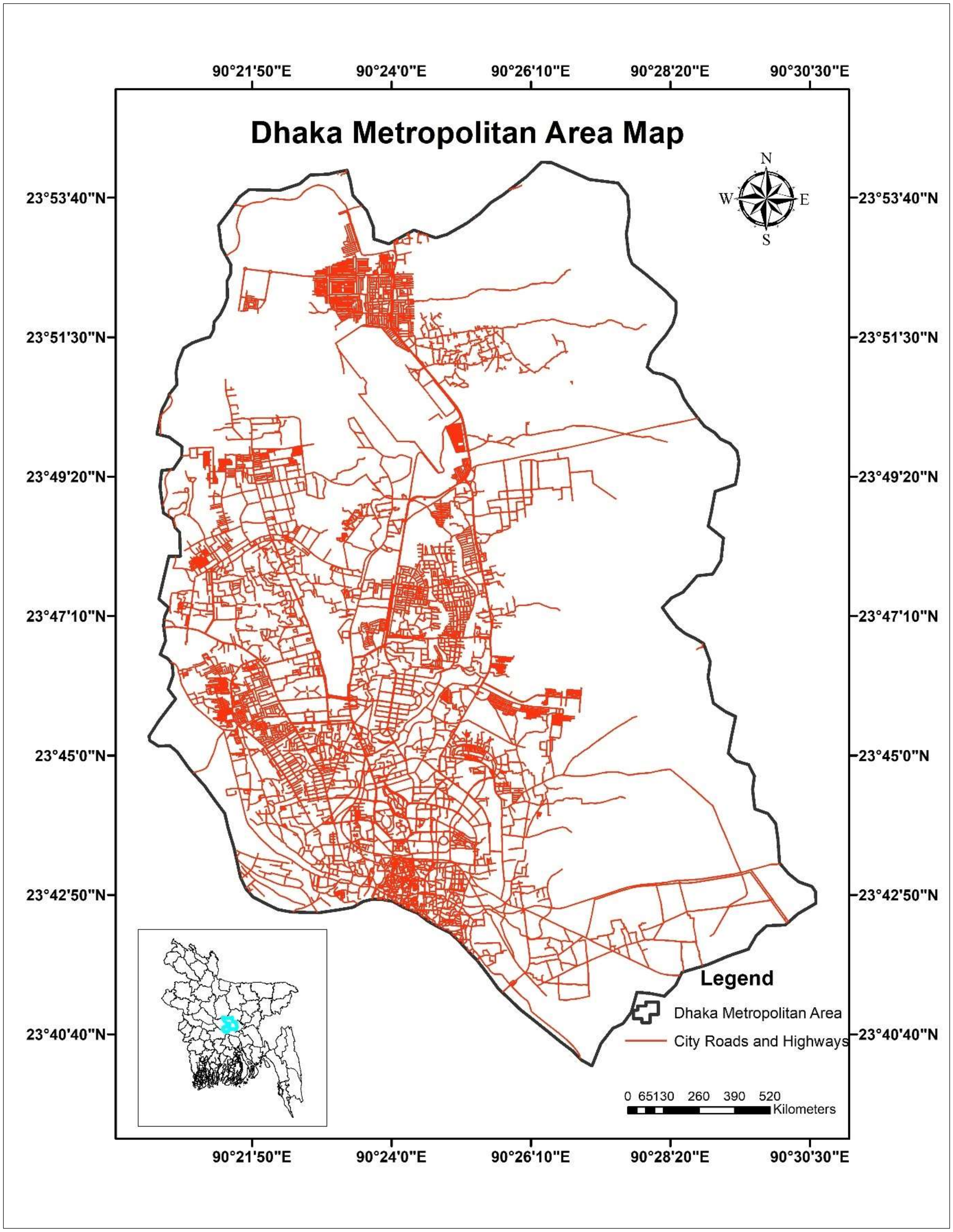

Figure 1. Dhaka Metropolitan Area (Study Area Map).

3.2 Data

This study examines collision data from the Accident Research Institute (ARI) of Bangladesh University of Engineering and Technology from 2015 to 2022 in the Dhaka Metropolitan Area (Figure 2, Figure 3 and Table 1). From 2015 to 2022, the data set comprises all police-reported accidents, including 2435 Accident Reporting Forms (ARFs) gathered from the Dhaka Metropolitan Police (DMP) Headquarters. About 73% of them are fatal accidents, while 29.7% are non-fatal. The number of fatal accidents fluctuated, peaking in 2015 with 290 instances and falling to 117 in 2020. Non-fatal accidents followed a similar path, with 102 reported in 2015 and expected to fall to 55 by 2020. The overall number of accidents changed, which might be attributed to increased road safety measures or changes in driving patterns. However, there was a significant rise in overall accidents from 2020 to 2022, going from 172 to 365 events, presumably owing to increased vehicular traffic, changes in road infrastructure, or changes in law enforcement techniques. The study underlines the need of investigating the root causes of these statistics in order to conduct targeted interventions, raise road safety awareness, and minimize the frequency of both fatal and non-fatal accidents in the future.

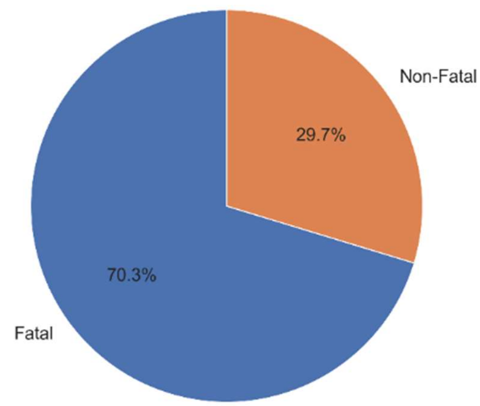

Figure 2. Dependent Variable Descriptive Statistics.

Table 1. Crash severity rate over the years (source: ARI, Buet).

Year	Fatal	Non-fatal	Total
2015	290	102	392
2016	242	91	333
2017	186	81	267
2018	195	78	273
2019	218	100	318
2020	117	55	172
2021	218	97	315
2022	246	119	365

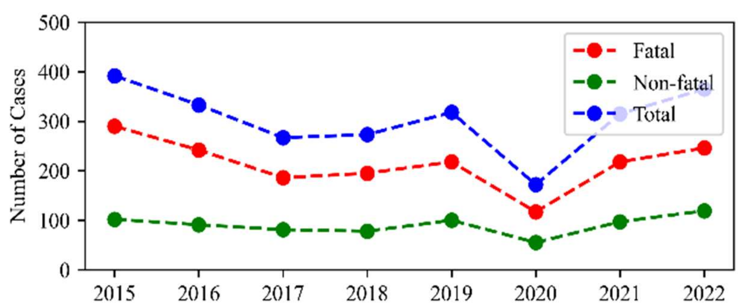

Figure 3. Crash severity trend over the years.

The collision database indicates four contributing causes to road accidents in Table 2: driver factors, vehicle factors, environmental factors, and road crash build environmental factors. The majority of accidents (70.3%) are caused by male drivers, with a greater proportion happening among drivers under the age of 50 (70.4%). Fatal accidents are more likely in situations involving intoxicated drivers (74.6%) and drivers who are not wearing seat belts (60.2%). Vehicle fitness certifications appear to reduce the number of deaths (64.5%). Motorized vehicles (70.4%) outnumber non-motorized vehicles (70.4%). Straight-ahead vehicles (72%) occur more frequently than other manoeuvres. Environmental variables have a considerable role, with accidents occurring more frequently at night (74.9%) and under good weather conditions (70.1%). Accidents are also more likely during the day (65.3%), at intersections (67.5%), and on routes with police control (69.6%). Environmental variables in traffic crashes are more common on straight and level roads (70.3%), with pedestrians being hit (77.7%). When compared to rural regions, urban areas have a larger number of accidents (70.1%), but roads with superior surface quality (70.9%) are more widespread.

Tabel 2. Descriptive Statistics of Independent Variables.

Variables	Category	Fatal Count (%)	Non-fatal Count (%)
Driver Factors			
Gender	Male = 1	1700 (70.3%)	719 (29.7%)
	Female = 0	12 (75%)	4 (25%)
Age	<50 years = 1	1664 (70.4%)	698 (29.6%)
	50 years > = 0	48 (65.8%)	25 (34.2%)
Injury	Fatal = 1	48 (92.3%)	4 (7.7%)
	Non-fatal = 0	1664 (69.8%)	719 (30.2%)
Alcohol	Drunk = 1	226 (74.6%)	77 (25.4%)
	Not drunk = 0	1486 (69.7%)	646 (30.3%)
Seat Belt	Wear = 1	153 (60.2%)	101 (39.8%)
	Not wear = 0	1559 (71.5%)	622 (28.5%)
Vehicle Factors			
Fitness	Yes = 1	844 (64.5%)	464 (35.5%)
Certificate	No = 0	868 (77%)	259 (23%)
Vehicle Type	Motorized (two-wheeler, three-wheeler, four-wheeler, etc.) = 1	1363 (70.4%)	574 (29.6%)
	Non-motorized (two-wheeler, three-wheeler, etc.) = 0	349 (70.1%)	149 (29.9%)
Vehicle	Going ahead=1,	1280 (72%)	497 (28%)
Maneuver	Others (left turn, right turn, u turn, etc.) = 0	432 (65.7%)	226 (34.3%)
Environmental Factors			
Time	Day (06:01 am - 06:00 pm) =1	851 (66.2%)	434 (33.8%)
	Night ((06:01 pm - 06:00 am) = 0	861 (74.9%)	289 (25.1%)
Weather	Good = 1	1651 (70.1%)	705 (29.9%)
	Others (rain, wind, fog) = 0	61 (77.2%)	18 (22.8%)
Light	Day light = 1	780 (65.3%)	415 (34.7%)
Condition	Others (dawn/dark, night little, night) = 0	932 (75.2%)	308 (24.8%)
Road Crash Build Environmental Factors			
Road	Straight + flat = 1	1558 (70.3%)	657 (29.7%)
Geometry	Others (curve + slope, crest, etc.) = 0	154 (70%)	66 (30%)
Junction Type	Junction (cross, t, staggered, roundabout, railway etc.) = 1	546 (67.5%)	263 (32.5%)
	Not a junction = 0	1166 (71.7%)	460 (28.3%)
Traffic	Police controlled=1	1002 (69.6%)	438 (30.4%)
Control	Others (pedestrian crossing, traffic lights, police + traffic lights, etc.) = 0	710 (71.4%)	285 (28.6%)
Collision	Hit pedestrian = 1	1183 (77.7%)	340 (22.3%)
Type	Others (head on, rear end, right angle, side swing, etc.) = 0	529 (58%)	383 (42%)
Movement	One way = 1	791 (71.5%)	316 (28.5%)
	Two ways = 0	921 (69.4%)	407 (30.6%)
Divider	Yes = 1	1222 (68.8%)	554 (31.2%)
	No = 0	490 (74.4%)	169 (25.6%)
	Urban = 1	1685 (70.1%)	720 (29.9%)

Location Type	Rural = 0	27 (90%)	3 (10%)
Surface	Good = 1	1622 (70.9%)	665 (29.1%)
Quality	Others (rough, under repair) = 0	90 (60.8%)	58 (39.2%)
Road Class	National = 1	711 (79.4%)	184 (20.6%)
	Others (regional, feeder, rural, city) = 0	1001 (65%)	539 (35%)

3.3 Correlation Matrix

A Pearson correlation matrix (Table 3) is a statistical tool that displays correlations between variables. Correlation coefficients are used to express the strength and direction of linear relationships, with -1 to 1 signifying negative, positive, or no correlations. To find significant differences between groups, a two-tailed test is performed. Significance labels reflect the statistical significance of correlations, which is commonly set at 0.05. The interpretation of this table assists researchers in understanding patterns between variables and making data-driven judgments.

3.4 Binary Logistic Regression Model

Binary logistic regression is a statistical approach for modeling the connection between a binary dependent variable and one or more independent variables. The dependent variable in our scenario is accident severity, which is either fatal or non-fatal (i.e., fatal=1, non-fatal=0), while the independent variables are binary. The logistic regression model maps any real-valued number into the range [0, 1] using the logistic function (also known as the sigmoid function). The logistic function equation is:

$$P(Y=1) = \frac{1}{1 + e^{-(b_o + b_1 X_1 + b_2 X_2 + \dots\dots + b_i X_i)}}$$

Where:

$P(Y=1)$ is the probability of the dependent variable being 1 (fatal accident). While e is the base of the natural logarithm (approximately equal to 2.71828), and b_o is the intercept (constant term) of the equation. And $b_1, b_2, \dots\dots\dots, b_i$ are the coefficients of the independent variables $X_1, X_2, \dots\dots\dots, X_i$ respectively.

The study was carried out using the RStudio program. The model was evaluated at a minimum significance level of 90% with a 10% margin of error to guarantee a solid comprehension. The fitness of the model was assessed using several statistical indicators such as Log-Likelihood, AIC, BIC, McFadden's R^2, Nagelkerke's R^2, Cox and Snell's R^2, and Efron's R^2. These indicators gave a thorough evaluation of the model's performance and aided in determining its overall fit. Furthermore, sensitivity tests were performed to assess the model's stability and dependability under various circumstances, bolstering the validity of the findings.

Table 3. Pearson

	Severity	Gender	Age	Injury	Alcohol	Seatbelt	Fitness	Vehicle	Maneuver	Time	Weather	Light	Geometry	Junction	Traffic	Collision	Movement	Divider	Location	Surface	Class
Severity	1.00																				
Gender	-0.01	1.00																			
Age	0.02	0.05*	1.00																		
Injury	0.07***	0.01	0.01	1.00																	
Alcohol	0.04	-0.02	0.00	0.05*	1.00																
Seatbelt	-0.08***	0.03	-0.04*	0.14***	0.03	1.00															
Fitness	-0.14***	-0.01	0.05*	-0.01	0.03	0.07***	1.00														
Vehicle	0.00	0.02	0.10***	-0.21***	0.01	-0.18***	0.18***	1.00													
Maneuver	0.06**	0.01	-0.01	-0.03	-0.12***	0.00	-0.13***	0.00	1.00												
Time	-0.09***	0.01	0.02	0.00	-0.04	0.02	0.06**	0.02	-0.01	1.00											
Weather	-0.03	-0.01	0.02	-0.02	0.00	0.01	0.03	0.00	0.00	0.05*	1.00										
Light	-0.11***	0.02	-0.01	0.01	0.00	0.04*	0.04*	0.00	-0.03	0.59***	0.00	1.00									
Geometry	0.00	-0.01	0.00	-0.04*	0.01	-0.01	-0.01	-0.01	0.05**	-0.03	0.05*	-0.01	1.00								
Junction	-0.04*	0.05*	0.07***	0.03	0.01	0.02	0.10***	0.06**	-0.04*	-0.01	-0.02	-0.01	-0.07***	1.00							
Traffic	-0.02	0.02	0.00	0.00	-0.04	-0.01	0.01	0.02	0.07**	0.03	0.03	0.02	0.06**	0.01	1.00						
Collision	0.21***	0.00	0.04*	-0.11***	0.01	-0.07***	-0.13***	-0.01	0.12***	-0.02	0.01	0.00	0.02	-0.02	0.05**	1.00					
Movement	0.02	0.00	0.00	0.00	0.00	0.03	-0.02	-0.02	-0.04*	-0.02	-0.01	-0.01	0.00	-0.03	-0.06**	-0.04	1.00				
Divider	-0.05**	-0.03	-0.01	0.01	-0.01	0.05*	-0.03	-0.02	0.04	-0.06**	0.00	-0.03	0.13***	0.01	0.06**	-0.04*	0.20***	1.00			
Location	-0.05*	-0.01	0.00	0.02	0.03	0.00	-0.01	-0.05*	-0.06**	-0.02	0.04*	0.00	0.03	-0.02	0.03	-0.02	0.02	0.06**	1.00		
Surface	0.05**	-0.02	0.01	0.01	0.00	0.00	-0.04*	-0.01	0.02	-0.01	0.00	-0.01	0.06**	-0.01	-0.02	-0.01	0.05**	0.07***	0.03	1.00	
Class	0.15***	-0.02	-0.01	0.02	-0.01	-0.06**	-0.04*	0.05**	0.03	-0.06**	-0.01	-0.02	-0.01	-0.05*	0.00	0.05*	0.11***	0.03	0.00	0.05*	1.00

*** Correlation is significant at the 0.001 level (2-tailed), ** Correlation is significant at the 0.01 level (2-tailed), * Correlation is significant at the 0.05 level (2-tailed)

Correlation Matrix.

4. RESULT AND DISCUSSION

4.1 Model Fitness

The model fitness and model estimates indicators in Table 2 provide insight into the statistical model's performance. A negative Log-Likelihood score of -1340.98 indicates a strong fit, implying that the model's predictions match the observed data well. The AIC, which balances model fit and complexity, is 2723.96, indicating a moderate fit, however the higher BIC value of 2845.71 indicates probable over-complexity. McFadden's R^2 of 0.095 indicates that the model explains approximately 9.5% of the variation in the data, indicating a reasonable fit. However, the model does not explain much variation, as indicated by Nagelkerke's R^2 and Cox and Snell's R^2 values of 0.000 and 0.001, respectively. Efron's R^2 of 0.109 indicates that the model accounts for about 10.9% of the data variation.

Tabel 1. Binary logistic regression model estimates.

Variables	Coefficient Estimate	Standard Error	t - Stat	p Value	Sig. Level
Constant (Intercept)	1.77	0.97	1.82	0.069	.
Driver Factors					
Gender (male=1, female=0)	-0.14	0.61	-0.24	0.811	
Age (<50 year=1, 50 year>=0)	0.15	0.27	0.56	0.578	
Injury (fatal=1, non-fatal=0)	2.30	0.54	4.23	0.000	***
Seat belt (worn=1, not worn=0)	-0.36	0.15	-2.41	0.016	*
Alcohol (drunk=1, not drunk=0)	0.29	0.15	1.94	0.053	.
Vehicle Factors					
Fitness certificate (yes=1, no=0)	-0.47	0.10	-4.68	0.000	***
Vehicle type (motorized=1, non-motorized=0)	0.18	0.12	1.45	0.148	
Vehicle maneuver (going ahead=1, others=0)	0.14	0.11	1.36	0.173	
Environmental Factors					
Time (day=1, night=0)	-0.15	0.12	-1.23	0.219	
Light (day light=1, others=0)	-0.41	0.12	-3.53	0.000	***
Weather (good=1, others=0)	-0.30	0.29	-1.06	0.291	
Road Crash Build Environmental Factors					
Road geometry (straight + flat=1, others=0)	0.05	0.17	0.28	0.781	
Junction type (junction=1, others=0)	-0.15	0.10	-1.46	0.144	
Collision type (hit pedestrian=1, others=0)	0.91	0.10	9.38	0.000	***
Traffic control (police controlled=1, others=0)	-0.09	0.10	-0.89	0.374	
Divider (yes=1, no=0)	-0.33	0.11	-2.94	0.003	**
Movement (1-way=1, 2-way=0)	0.11	0.10	1.13	0.257	
Location type (urban=1, rural=0)	-1.23	0.62	-1.99	0.047	*
Road class (national=1, others=0)	0.67	0.10	6.44	0.000	***
Surface quality (good=1, others=0)	0.43	0.19	2.29	0.022	*
Model Fitness					
Log-Likelihood: -1340.98					
AIC: 2723.96					
BIC: 2845.71					
McFadden's R^2: 0.095					
Nagelkerke's R^2: 0.000					
Cox and Snell's R^2: 0.001					
Efron's R^2: 0.109					
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					

4.2 Driver Factors

The influence of driver gender on road safety is negligible, indicated by a non-significant coefficient of -0.14 (p-value = 0.811). In practical terms, male drivers face 2.3 times higher odds of being in a road accident compared to their female counterparts. Driver age, with a coefficient of 0.15 and a non-significant p-value of 0.578, holds a limited impact. Drivers under 50 years old encounter 1.8 times higher odds of being in a road accident than those aged 50 and above. The severity of driver injury significantly affects accident involvement, reflected in a substantial negative coefficient of -2.3 (p-value = 0.000). Fatally injured drivers have 2.3 times higher odds of being in a road accident compared to non-fatally injured drivers. Seat belt usage plays a crucial role, as evidenced by a significant negative coefficient of -0.36 (p-value = 0.016). Drivers who wear seat belts experience 0.36 times lower odds of being in fatal accidents compared to their non-seat belt-wearing counterparts. Alcohol consumption amplifies accident risk, supported by a significant positive coefficient of 0.29 (p-value = 0.053). Drivers involved in accidents after consuming alcohol face 0.29 times lower odds of fatal outcomes compared to non-alcohol-consuming drivers.

4.3 Vehicle Factors

The coefficient for the time shift when accidents occur is -0.47, though it lacks statistical significance (p-value = 0.000). Drivers possessing valid vehicle fitness certificates exhibit a 0.47 times lower likelihood of being involved in fatal accidents compared to those without proper certification. Vehicle types play a role, albeit insignificantly, with a positive coefficient of 0.18 (p-value = 0.148). Motorized vehicle operators, encompassing two-wheelers, three-wheelers, and four-wheelers, face 0.18 times higher odds of being in fatal accidents than drivers of non-motorized vehicles like bicycles or pedestrians. Vehicle maneuver impacts accident probabilities, indicated by a non-significant positive coefficient of 0.14 (p-value = 0.173). Drivers who proceed straight experience a 0.14 times reduced likelihood of being in fatal accidents compared to those executing other maneuvers such as left turns, right turns, or U-turns.

4.4 Environmental Factors

The coefficient for the time shift of accidents stands at -0.15, although it lacks statistical significance (p-value = 0.219). This implies that the time of day does not significantly influence the odds of an accident being fatal at a rate of 0.15 times. However, the negative coefficient suggests that accidents occurring during the day have slightly lower odds of being fatal compared to those during the night. Accidents that happen in daylight hours are associated with a significant negative coefficient of -0.41 (p-value = 0.000). Drivers involved in daytime accidents have 0.41 times the odds of being in fatal accidents compared to accidents occurring at other times of the day, such as dawn, dusk, or nighttime. Weather conditions during accidents show a non-significant negative coefficient of -0.30 (p-value = 0.291). Accidents in good weather conditions are associated with 0.30 lower odds of being fatal compared to accidents in adverse weather conditions like rain, wind, or fog.

4.5 Road Crash Build Environmental Factors

The positive coefficient value of 0.05 for roadway geometry indicates a statistically insignificant p-value of 0.781. This suggests that roadways with straight and flat geometry are 0.05 times less likely to be fatal compared to roadways with other geometry types (such as curves, slopes, and crests). The negative coefficient value of -0.15 for roadway junction type comes with a statistically insignificant p-value of 0.144. This implies that collisions involving vehicles hitting pedestrians at junctions have 0.15 times lower odds of being fatal compared to collisions at other types of junctions, including crossroads, T-junctions, staggered junctions, roundabouts, and railway crossings. The positive coefficient of 0.91 for collision type has a statistically significant p-value of 0.000. This indicates that collisions involving vehicles hitting pedestrians are 0.91 times less likely to be fatal compared to other types of collisions such as head-on, rear-end, right-angle, and side-swing collisions. The negative coefficient value of -0.09 for traffic control has a statistically significant p-value of 0.000. This suggests that collisions occurring at locations where traffic is controlled by police are 0.09 times less likely to be fatal compared to collisions at locations with other types of controls like pedestrian crossings, traffic lights, or a combination of police and traffic lights. The negative coefficient value of -0.33 for road divider has a statistically significant p-value of 0.003. This implies that roadways with dividers are 0.33 times less likely to be fatal compared to roadways without dividers. The positive coefficient value of 0.11 for vehicle movement type comes with a statistically insignificant p-value of 0.257. This suggests that collisions involving one-way vehicle movement have 0.43 times lower odds of being fatal compared to collisions involving two-way movement, although this result is not statistically significant. The negative coefficient value of -1.23 for location type is statistically significant with a p-value of 0.047. This means that road crashes on urban roads have 0.43 times lower odds of being fatal compared to road crashes on rural roads. The positive coefficient value of 0.67 for road class is statistically significant with a p-value of 0.000. This implies that a one-unit increase in road class increases the log odds of a fatal road crash by 0.67. Therefore, roads with higher class rankings have 0.43 times lower odds of being fatal compared to roads with lower rankings such as regional, rural, feeder, and city roads. The positive coefficient value of 0.43 for road surface quality is statistically significant with a p-value of 0.022. This indicates that a one-unit increase in road surface quality is associated with a 0.43 increase in the log odds of a fatal road crash. Hence, roads with better surface quality have 0.43 times lower odds of being fatal compared to roads with poor surface quality.

5. CONCLUSION

The purpose of this study was to determine the effect of driver, vehicle, environmental, and road accident design elements on the likelihood of fatal and non-fatal road collisions. According to the findings, driver injury, seat belt use, and alcohol use all had a substantial impact on road safety outcomes. Furthermore, small but statistically insignificant impacts are seen for vehicle fitness certification, vehicle type, and vehicle maneuver. The severity of road collisions is also affected by environmental factors such as time of day, weather conditions, and road surface quality. Furthermore, roadway geometry, roadway junction type, collision type, traffic management, road divider, vehicle movement type, location type, road class, and road surface quality were found to have a strong link with fatal road collisions.

These findings imply that a comprehensive strategy to road safety initiatives, including both driver and environmental variables, is required. Specific interventions could include:

- Promoting seat belt use and reducing drunk driving;
- Ensuring vehicle maintenance and certification;
- Improving road infrastructure and traffic management systems; and
- Educating drivers about road safety and how to reduce their risk of being involved in a fatal crash.

Policymakers and practitioners can minimize the incidence of fatal road collisions and enhance overall road safety by addressing these variables.

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REFERENCES

[1] WHO: Global status report on road safety 2018.

[2] Md. M. Hoque and M. F. Salehin, “Vulnerable Road Users (VRUs) Safety in Bangladesh,” 16th Road Safety on Four Continents Conference, May 2013.

[3] S. Pervaz, S. Hazanat-E-Rabbi, and K. M. S. Newaz, “Pedestrian safety at intersections in Dhaka metropolitan city,” 2016.

[4] S. Yasmin, N. Eluru, and S. V. Ukkusuri, “Alternative Ordered Response Frameworks for Examining Pedestrian Injury Severity in New York City,” Journal of Transportation Safety & Security, vol. 6, no. 4, pp. 275–300, 2014, doi: 10.1080/19439962.2013.839590.

[5] M. Uddin and F. Ahmed, “Pedestrian Injury Severity Analysis in Motor Vehicle Crashes in Ohio,” Safety 2018, Vol. 4, Page 20, vol. 4, no. 2, p. 20, May 2018, doi: 10.3390/SAFETY4020020.

[6] K. Haleem, P. Alluri, and A. Gan, “Analyzing pedestrian crash injury severity at signalized and non-signalized locations,” Accid Anal Prev, vol. 81, pp. 14–23, Aug. 2015, doi: 10.1016/J.AAP.2015.04.025.

[7] G. S. Tulu, S. Washington, M. M. Haque, and M. J. King, “Injury severity of pedestrians involved in road traffic crashes in Addis Ababa, Ethiopia,” Journal of Transportation Safety & Security, vol. 9, pp. 47–66, Mar. 2017, doi: 10.1080/19439962.2016.1199622.

[8] N. N. Sze and S. C. Wong, “Diagnostic analysis of the logistic model for pedestrian injury severity in traffic crashes,” Accid Anal Prev, vol. 39, no. 6, pp. 1267–1278, Nov. 2007, doi: 10.1016/J.AAP.2007.03.017.

[9] A. Ariffin, Z. Jawi, … K. K.-P. of the, and undefined 2011, “Man vs. Vehicle-A Look into Risk Factors Associated with Pedestrian Injury Severity in Road Accidents in Malaysia,” jstage.jst.go.jpAH Ariffin, ZM Jawi, KAA Kassim, SV WongProceedings of the Eastern Asia Society for Transportation Studies Vol, 2011•jstage.jst.go.jp, vol. 8, 2011.

[10] S. Sarkar, R. Tay, and J. D. Hunt, “Logistic Regression Model of Risk of Fatality in Vehicle–Pedestrian Crashes on National Highways in Bangladesh,” https://doi.org/10.3141/2264-15, no. 2264, pp. 128–137, Jan. 2011, doi: 10.3141/2264-15.

[11] N. M. Zafri, A. A. Prithul, I. Baral, and M. Rahman, “Exploring the factors influencing pedestrian-vehicle crash severity in Dhaka, Bangladesh,” Int J Inj Contr Saf Promot, vol. 27, no. 3, pp. 300–307, Jul. 2020, doi: 10.1080/17457300.2020.1774618.

[12] K. Haleem, P. Alluri, and A. Gan, “Analyzing pedestrian crash injury severity at signalized and non-signalized locations,” Accid Anal Prev, vol. 81, pp. 14–23, Aug. 2015, doi: 10.1016/J.AAP.2015.04.025.

[13] K. Obeng, M. Rokonuzzaman, K. Obeng, and M. Rokonuzzaman, “Pedestrian Injury Severity in Automobile Crashes,” Open Journal of Safety Science and Technology, vol. 3, no. 2, pp. 9–17, Jun. 2013, doi: 10.4236/OJSST.2013.32002.

[14] Z. Chen and W. (David) Fan, “A multinomial logit model of pedestrian-vehicle crash severity in North Carolina,” International Journal of Transportation Science and Technology, vol. 8, no. 1, pp. 43–52, Mar. 2019, doi: 10.1016/J.IJTST.2018.10.001.

[15] R. Amoh-Gyimah, E. N. Aidoo, M. A. Akaateba, and S. K. Appiah, “The effect of natural and built environmental characteristics on pedestrian-vehicle crash severity in Ghana,” Int J Inj Contr Saf Promot, vol. 24, no. 4, pp. 459–468, Oct. 2017, doi: 10.1080/17457300.2016.1232274.

[16] S. M. Rifaat and H. C. Chin, “Accident severity analysis using ordered probit model,” J Adv Transp, vol. 41, no. 1, pp. 91–114, 2007, doi: 10.1002/ATR.5670410107.

[17] S. Sarkar, R. Tay, and J. D. Hunt, “Logistic Regression Model of Risk of Fatality in Vehicle–Pedestrian Crashes on National Highways in Bangladesh,” https://doi.org/10.3141/2264-15, no. 2264, pp. 128–137, Jan. 2011, doi: 10.3141/2264-15.

[18] N. N. Sze and S. C. Wong, “Diagnostic analysis of the logistic model for pedestrian injury severity in traffic crashes,” Accid Anal Prev, vol. 39, no. 6, pp. 1267–1278, Nov. 2007, doi: 10.1016/J.AAP.2007.03.017.

[19] M. Pour-Rouholamin and H. Zhou, “Investigating the risk factors associated with pedestrian injury severity in Illinois,” J Safety Res, vol. 57, pp. 9–17, Jun. 2016, doi: 10.1016/J.JSR.2016.03.004.

[20] C. Xin, R. Guo, Z. Wang, Q. Lu, and P. S. Lin, “The effects of neighborhood characteristics and the built environment on pedestrian injury severity: A random parameters generalized ordered probability model with heterogeneity in means and variances,” Anal Methods Accid Res, vol. 16, pp. 117–132, Dec. 2017, doi: 10.1016/J.AMAR.2017.10.001.

[21] E. Jiménez-Mejías, V. Martínez-Ruiz, C. Amezcua-Prieto, R. Olmedo-Requena, J. D. D. Luna-Del-Castillo, and P. Lardelli-Claret, “Pedestrian- and driver-related factors associated with the risk of causing collisions involving pedestrians in Spain,” Accid Anal Prev, vol. 92, pp. 211–218, Jul. 2016, doi: 10.1016/J.AAP.2016.03.021.

[22] C. V. Zegeer and M. Bushell, “Pedestrian crash trends and potential countermeasures from around the world,” Accid Anal Prev, vol. 44, no. 1, pp. 3–11, Jan. 2012, doi: 10.1016/J.AAP.2010.12.007.

[23] N. N. Sze and S. C. Wong, "Diagnostic analysis of the logistic model for pedestrian injury severity in traffic crashes," Accid Anal Prev, vol. 39, no. 6, pp. 1267–1278, Nov. 2007, doi: 10.1016/J.AAP.2007.03.017.