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ANALYZING THE FACTORS INFLUENCING ROAD TRAFFIC ACCIDENT SEVERITY: A CASE STUDY OF KHULNA CITY

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ABSTRACT

Road traffic accident occurrences are terrible global phenomena all over the world. With more and different motorized vehicles, Bangladesh and Khulna city face a more significant number of fatalities and injuries. The metropolitan city is one of the riskiest places for road accidents because of its higher population density than in any other location. Road accidents in Khulna city are a significant problem, and they are increasing day by day. So, to reduce the severity of road accidents, the factors influencing road accident severity in Khulna city must be studied and analyzed. Binomial logistic regression is selected and applied to predict the risk or severity of 266 accidents from 2010 to 2019, collected by the Traffic Branch of the Deputy Police Commissioner of Khulna Metropolitan Police. The response variable for this study is accident severity (fatal and non-fatal). According to the study's findings, the number of injuries, number of fatalities, vehicle velocity, accident time, collision type, type of vehicle, and vehicle ownership influence the severity of road traffic accidents in Khulna. This study and its recommendations will aid in developing and implementing future road traffic policies and safety measures.

KEYWORDS: Accident risk; Road Traffic Accident (RTA); accident severity; binomial logistic regression; Khulna city.

1. INTRODUCTION

Road and traffic collisions or accidents are complicated globally because of financial and health-related issues. The global widespread fatalities and disabilities caused by road accidents are gradually being recognized as a major public health concern. Every year, over 1.2 million people are died on the world's roads, with an additional 20 to 50 million suffering non-fatal injuries (WHO, 2015). According to Rezaur, Adhikary, Hossain, and Wan Ibrahim (2005), 70% of road traffic deaths occurred in developing countries; 65% were pedestrians, and 35% were children. About 15 million to 20 million people suffer severe injuries (Rezaur et al., 2005). The World Health Organization undertook an observational epidemiological study where Harvard University and the World Bank showed that the world's ninth biggest cause of death during the 1990s was traffic accidents (WHO, 2015). Road accidents are among the most severe causes of death or fatality, with over 1.4 million people perishing on roads in 2016, and 74% of these are male fatalities (Benlagha & Charfeddine, 2019). According to WHO (2015), 90% of global road traffic deaths occur in low-income and middle-income countries. Low and middle-income countries have higher road traffic fatality rates of 21.5 and 19.5 for every 100,000 population, respectively, than high-income countries, which have a fatality rate of 10.3 for every 100,000 population. The Asia-Pacific region contributes to nearly 60% of the deaths of only half of the world's registered motorized vehicles (Chen, Wang, Wu, Chen, & Zegras, 2017). In the Southeast Asia region, the traffic fatality rate is 16.6 out of every 100,000 people, and pedestrians have a 90% chance of surviving a car crash at or below 30 km/h. A 50% chance of surviving the impact of an accident remains above the 40 km/h speed limit (WHO, 2015). In Japan, road traffic accidents accounted for 5,73,842 in 2014; 19,204 were single-vehicle accidents, accounting for around 3.3% of the total (Nakai & Usui, 2017). Another 96.7% of accidents occurred in modes other than single vehicles (Nakai & Usui, 2017). In India, 2 million people have a disability that results from a road traffic crash (WHO, 2015).

Haque and Mahmud (2009) stated that registered motor vehicle registration had increased about 210% on the road in Bangladesh in 17 years. Approximately 75% of passengers and 65% of freight movement occurs on the road system. 4,114 road accidents happened in 2003, and the number of deaths was 3,334, while 3,740 people were injured (Maniruzzaman & Mitra, 2005). Bangladesh has one of the highest road accident fatalities globally, with over 100 deaths for every 10,000 vehicles (Haque & Mahmud, 2009). Pedestrians were involved in about 60% of road fatalities in urban areas, while rural pedestrians accounted for 40% of total road traffic accidents (Hoque, 1991). Dhaka, Chittagong, Khulna, and Rajshahi account for about 20% of road accidents (Hoque, 1991). Khulna is a central industrial and divisional hub and is the third-largest city in Bangladesh (Rezaur et al., 2005; Sahriar, Hossain, Zarin, & Sarkar, 2020). The land size of the Khulna City area is 45.65 square kilometers, with a population of 1.5 million, with a population density of 26,287 in each square kilometer (Rezaur et al., 2005; Sahriar et al., 2020). Khulna City Corporation has 243 kilometers of roadways, including 158 kilometers of bituminous road, 67 kilometers of HBB (Herring Bone Bond) road, and 18 kilometers of the earthen road (BBS, 2013). Rickshaws and other non-motorized transport modes account for 60% of total traffic flow in Khulna city (Rezaur et al., 2005). The total number of vehicles on the road in Khulna city is over 20,990, of which 63.6% are non-motorized, and 36.4% are motorized, with a 15% annual growth rate for motorized vehicles (Uddin & Sen, 2004). This research discovers and examines the indicators that affect road traffic accident severity in Khulna city using a mathematical modeling approach.

2. LITERATURE REVIEW

Road traffic accident-related literature has provided many qualitative or quantitive approaches to address accident events (Garder, 2004; Li, 2013; Zhang, Yau, & Chen, 2013). The literature of quantitive research has been found to investigate accident severity, frequency, analyzing factors, etcetera (Garder, 2004; Li, 2013; Zhang et al., 2013). Researchers inspect the factors that influence or impact road accidents (Garder, 2004; Martin, 2002). To investigate these types of risk or impact factors and the severity of accidents, researchers have used different statistical and spatial tools to model the circumstances of the accident. They have used different modeling approaches. These factors and the modeling approaches are described in this section.

2.1 Prominent Factors Affecting Road Accident Severity

Li (2013) introduced three factors that affect road traffic accident events: traffic characteristics, road network and infrastructure, and demographic and environmental characteristics. Jahan (2019) also presented three factors influencing the severity of highway accidents: road and environmental factors, vehicle factors, and human error. According to Zhang et al. (2013), the main variables for road traffic casualties are gender (male, female, or transgender), age of the drivers, vehicle condition, inappropriate safety status, overloading, poor visibility, insufficient street lighting, weekends, passenger vehicles, driver experience, morning rush hour, and severe weather.

A common assumption about how traffic interventions act on road accidents is that the high speed of vehicles, free flow, and low density are associated with more severe accidents (Li, 2013). In Maine, the USA, Garder (2004) found that 21 fatal crashes happened when the speed limit was 40 km/h or lower; 7 fatal crashes occurred when the speed of the vehicle was 48 km/hour; 21 fatal crashes in 56 km/hour; 3 fatal crashes in 64 km/hour; 16 fatal crashes in 72 km/hour. Speed plays a vital role in road traffic accidents in visual appearance. Road traffic accidents happen with increased vehicular speed (Garder, 2004). Martin (2002) showed that road traffic accident rates were highest and most significant in light traffic on French interurban motorways. Golob, Recker, and Alvarez (2004) showed that traffic volume had more influence on accident severity than speed. Three major vehicle types, known as passenger vehicles, goods vehicles, and motorcycles, are essential in analyzing the risk of road traffic accidents (Zhang et al., 2013).

Factors such as population, employment, age, and gender reflect an area's social structure and economic activities connected to accidents (Li, 2013). There are eight environmental factors: street-light condition, weather, visibility level, time of day, season, and year of the accident (Zhang et al., 2013). Zhang et al. (2013) stated the time of day into six categories according to working time patterns and people's lifestyles in China: 00:00–06:59 (midnight to dawn), 07:00–08:59 (morning rush hours), 09:00–11:59 (morning working hours), 12:00–16:59 (afternoon working hours), 17:00–19:59 (afternoon rush hours), and 20:00–23:59 (night time). Zhang et al. (2013) defined seasons into four broad categories: Spring (March to May), Summer (June to September), Autumn (October to November), and winter (December to February). In different seasons and different environmental perspectives, the risk of road traffic accidents differs (Zhang et al., 2013). Wang, Liu, Ma, Zhang, and Cong (2019) found that about 60% of the increment in motorized vehicles occurred and increased day by day in China.

The age of the vehicle at fault, the involvement of two different transport modes, the condition of a vehicle's tools, and the vehicle license are all indicators of the occurrence of road accidents (Malyshkina & Mannering, 2010; Jahan, 2019). Motorized vehicles are riskier than other vehicular modes. For example, motorcycles and their smaller size allow more mobility, especially in congested areas, making them more at risk for road traffic accidents (Moeinaddini, Asadi-Shekari, Sultan, & Shah, 2015; Nguyen, Hanaoka, & Kawasaki, 2014). Pedestrians are also considered a transport mode (Hijar, 2000). Non-motorized vehicle accident severity directly or indirectly depends on motorized vehicles and various road traffic accident factors (Hijar, 2000). From 2008 to 2012 in Japan, the injuries or deaths of pedestrians and cyclists were significant (Hijar, 2000). Hijar (2000) found that, despite traffic signals, pedestrian accidents occurred at intersections, such as in the crosswalk.

2.2 Applied logit models used in road traffic accident analysis

Regression analysis or models analyze risk, impact, prediction, or probability. It is known that regression is the perfect tool for predicting response variables when considering independent variables. When we look forward to modeling an accidental risk, effect, or severity, logit regression models are the optimum options for considering discrete qualitative variables (Jahan, 2019). The use and application of logistic regression models in unique accident analyzes have been given there, who use logit regression to analyze the risk and severity of road traffic accidents. Among other regressions, logistic regression applies to accident-related data to examine the contribution of several variables to accident severity (Al-Ghamidi, 2002). Al-Ghamidi (2002) used logistic regression to estimate accident severity and the influence of accident factors. As his response variable was binary, he selected the logistic regression model. He showed that logistic regression could be a promising tool for predicting probability, used for future safety improvements or policymaking. Champahom et al. (2020) also used the logistic regression model, where the probable outcome was to show the reason behind rear-end crashes through explanatory variables.

However, when the response variable has two categories, one can use the binary or binomial logit model. Al-Ghamidi (2002) used the binary logit model, where his response variables were binary, fatal, and non-fatal. The logistic regression technique is a perfect tool to assess the most critical factors contributing to the severity of road accidents (Al-Ghamidi, 2002). Eboli, Forciniti, and Mazzulla (2020), Tay (2016), Schlogl, Stutz, Laaha, and Melcher (2019), and Sze, Wong, and Lee (2014) also used binary logistic regression for their research for analyzing the factors influencing traffic accident severity.

A multinomial logistic regression model predicts a categorical dependent variable from a set of explanatory variables that might be dichotomous or continuous. (Starkweather & Moske, 2011). The multinomial logistic regression model extends the binomial logistic model by adding two-variable response categories (Starkweather & Moske, 2011). It is essential to evaluate multicollinearity with simple correlations in this regression model (Starkweather & Moske, 2011). Chen and Fan (2019) used multinomial logistic regression to assess the crash severity of pedestrians versus vehicles to identify significant factors that determine the pedestrian-vehicle crash severity. Murata (2015), Murray, Wernstedt, and Yin (2014), and Zeng et al. (2017) also used the multinomial logit approach for their research.

Different authors used mixed logit models in their research (Liu & Fan, 2020; Wu et al., 2014; Milton, Shankar, & Mannering, 2008). The central theme is the randomness of explanatory or independent variables (Jahan, 2019). Wu et al. (2014) investigated crashes occurring for incapable drivers on two-lane rural roads. They used mixed logit models to analyze driver injury severities in single-vehicle and multi-vehicle crashes on rural two-lane highways. Milton et al. (2008) used the mixed logit model for road accident severities. Their model allows for where estimated model parameters can vary randomly across different roadway segments (Milton et al., 2008). The multinomial logistic regression model does not work well when alternatives are not independent. There are taste variations among individuals; this problem is called the IIA property of independence of irrelevant alternatives (Hensher & Greene, 2002). The nested logit model extends the simple multinomial logistic regression model, where a single maximum likelihood function is planned and maximized (Hensher & Greene, 2002). Patil, Geedipally, and Lord (2012) used this model for analyzing crash severity.

3. METHOD

3.1 Study Area

According to BBS (2013), Khulna City Corporation has 243 kilometers of roadways, the optimum number of roads for this research. So, it's a good indicator to have a good number of accidents, and this is also a district and a divisional city. The roads and highways of Khulna city have great importance in economic, social, political, environmental, and human health-related phenomena (Rezaur et al., 2005). So, more traffic and road accidents are common phenomena in this city. For these reasons, we selected Khulna city as our study area. Figure 1 shows the study area (Khulna city) of this research.

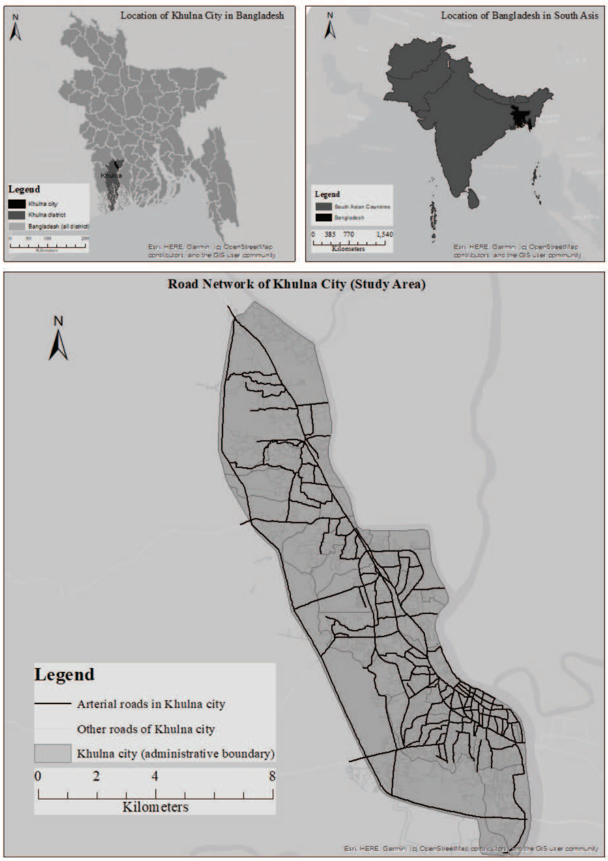

Figure 1: Map of Khulna city (study area)
Source: Authors, 2021

3.2 Data Classification

This study used ten years of (2010 to 2019) secondary road accident data collected from the traffic branch of the Deputy Police Commissioner of Khulna Metropolitan Police. In Khulna city, different police stations collect road accident data. Khulna Metropolitan Police's traffic division manages and stores registered road traffic accident data from various police stations. Every police station gathers information on road traffic accidents within its jurisdiction. The authors have converted Bengali data to the English format and sorted the data into IBM SPSS v26. The authors reformed and categorized the data and then used it. After cleaning and classifying the data, the authors filtered the variables and applied the final variables to get an acceptable outcome. Table 1 shows the details of the variables.

Table 1: List of variables

Variables	Description	Literature
Accident season	Categorical-ordinal (different seasons during accident) 1. Summer (mid-april to mid-june) 2. Rainy season (mid-june to mid-august) 3. Autumn (mid-august to mid-october) 4. Late autumn (mid-october to mid-december) 5. Winter (mid-december to mid-february) 6. Spring (mid-february to mid-april)	Zhang et al. (2013)
Accident time	Categorical-ordinal (Different categories of the period during accident occurrences) 1. Midnight to down (0.00 to 6.59) 2. Morning rush hours (7.00 to 8.59) 3. Morning working hours (9.00 to 11.59) 4. Afternoon working hours (12.00 to 16.59) 5. Afternoon rush hours (17.00 to 19.59) 6. Night-time (20.00 to 23.59)	Zhang et al. (2013)
Location of Accident	Categorical-nominal (Locations where accident events happen) 1. Sonadanga 2. Khan Jahan Ali Thana 3. Khulna Sadar Thana 4. Labonchora 5. Aranghata 6. Khalishpur 7. Daulatpur	Haque (1991)
Number of Fatalities	Ratio (Total number of fatalities during an accident)	Anjuman, Hasanat-E-Rabbi, Siddiqui, and Hoque (2020)
Number of injuries	Ratio (Total number of injuries during an accident)	

Table 1: List of variables (continued)

Variables	Description	Literature
Reason behind accident	Categorical-nominal (Reasons behind accident events) 1. Pedestrian accident 2. Motorcycle accident 3. Truck driving at higher speed 4. Crossing collision 5. Losing balance between speed	Anjuman et al. (2020)
Reported status of an accident	Categorical-nominal (Different reporting status reported by traffic branch of Khulna Metropolitan Police) 1. Died under treatment 2. Died on the spot 3. Grievously injured 4. Died on the spot & grievous injury 5. Minor injury 6. No-injury	Author's compilation
Type of vehicles	Categorical-nominal (Types of the vehicles during accident) 1. Bus 2. Pickup truck 3. Private car 4. Motorcycle 5. Truck	George et al. (2017), and Moeinaddini et al. (2015)
Vehicle Ownership	Categorical-nominal (Ownership of vehicle, either public or private) 1. Private 2. Public	Singh and Misra (2004)
Type of collision	Categorical-nominal (Types of collisions related to vehicles during accidents) 1. Road-cross collision 2. Rear-end collision 3. High-speed collision 4. Head-on collision 5. Side-swipe collision	Anjuman et al. (2020)
Type of injury	Categorical-nominal (Injury occurred by accident events) 1. Grievous 2. Minor injury 3. No-injury	Jahan (2019)
Velocity of vehicle	Categorical-ordinal (Vehicular speed during accident) 1. Below 40km/hour 2. Above 40km/hour	Uddin and Sen (2004), and Garder (2004)

Source: Authors, 2021

3.3 Analytical Procedure

This study tries to contribute to the comprehension of the severity of road accidents and forecast the relationship between modes of transportation and accident severity in Khulna. Figure 2 depicts the analytical framework of this research to analyze a way to find out the road accident risk or severity. Two essential steps for any research are variable selection, and the model's conducting. First, the authors have reviewed the literature to find relevant variables and have merged them with the collected data. This form of variable has been the primary variable. The final variables for the multinomial logistic regression model have been chosen from these primary variables using three different statistical tests: the collinearity test, cell frequency for each predictor variable compared to the response variable, accident severity, and finally, a likelihood ratio test has been conducted to identify and select the fitness of the data and the significance of predictor variables. After the final selection of variables, the binomial logistic regression model was run and used to show the impact of road traffic accident severity in Khulna.

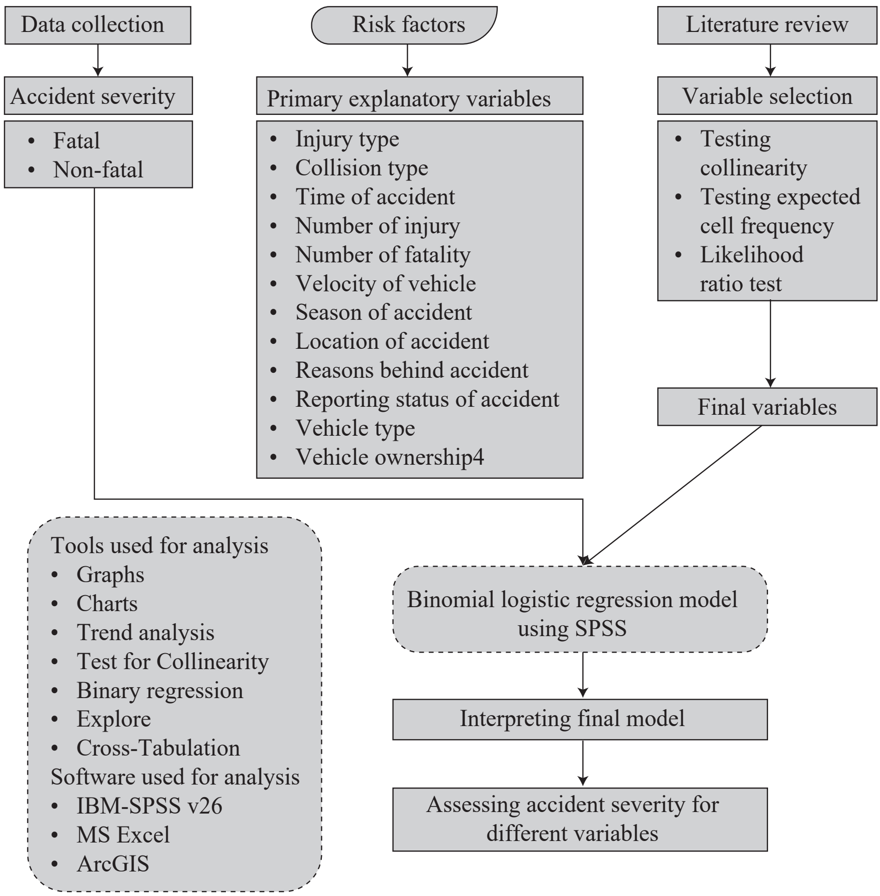

Figure 2: Analytical framework
Source: Authors, 2022

3.4 Method Selection

We have taken a quantitative approach to the analytical procedure for this study. The logistic regression models are very compatible with obtaining the outcome as probability, impact, the relationship between variables, or even predicting the riskier level among different levels of a variable (Murata et al., 2015; Garson, 2014). There are various logistic regression models like the binomial logistic model, multinomial logistic model, mixed logistic model, ordered logistic model, nested logistic model, and probit logistic model (Washington, Karlaftis, & Mannering, 2020). We selected the binomial logistic model, as the response variable has two possible discrete outcomes. The binomial logistic model has been used to predict the probabilities of road traffic accident severity in the two categories, either fatal or non-fatal. There is a selected set of explanatory variables that have been established in the analysis section.

3.4.1 The equation for the binomial logistic model

The binomial logistic model offers two possible categorical outcomes and estimates the probability of the categories. For this reason, we have used this model for this research. It calculates and interprets the chance of occurring a specific event compared to not happening that event through odds ratio or exp(β). However, the equation of odds ratio is:

$\textit{Odds ratio} = \frac{\textit{probability of occurring an event}}{1\textit{-probability of occurring an event}}$ .....(i) (Berenson, Szabat, & Krehbiel, 2012; Harrell, 2001)

Logistic regression models have based on the natural logarithm of the odds ratio. The equation of "k" explanatory or independent variable is:

$ln(\textit{estimated odds ratio}) = \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \ldots\ldots + \beta_k X_{ki} + \epsilon_i$ ... (ii) (Berenson et. al., 2012; Harrell, 2001; Schüppert, 2009)

Where k= number of predictor variables in the model; β_1= line gradient; β_k= regression coefficient of X_k; X_1, X_2, X_3… X_k = predictor variables; and ϵ_i = random error in *i* observation.

So, (*Estimated odds ratio*) = $e^{ln\ (Estimated\ odds\ ratio)}$…(iii) (Berenson et. al., 2012; Harrell, 2001)

As logistic regression most likely use the maximum likelihood technique, and the levels of the dichotomous dependent variable are fatal and non-fatal, the equation can be stated as follows:

$ln\left(\frac{p(fatal)}{p(nonfatal)}\right) = \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \ldots\ldots + \beta_k X_{ki} + \epsilon_i$ ... (iv)

$\Rightarrow ln\left(\frac{p(fatal)}{p(nonfatal)}\right) = \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \ldots\ldots + \beta_k X_{ki} + \epsilon_i$ ... (v) (Al-Ghamdi, 2002; Schüppert, 2009)

$\Rightarrow P = \frac{e^{\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_k X_{ki} + e}}{1 + e^{\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_k X_{ki} + e}}$>...(vi) (Al-Ghamdi, 2002; Schüppert, 2009)

There,

P = probability of fatal accident; and

1 - *P = probability of fatal accident.*

4. ANALYSIS AND INTERPRETATIONS

According to registered data collected from the traffic branch of the Deputy Police Commissioner of Khulna Metropolitan Police, 266 accidents occurred in Khulna city between 2010 and 2019, with 198 fatalities among them. According to the data, 26 accidents occur each year in Khulna, and 19 people are killed. However, from 2010 to 2019, the locations of road traffic accidents are depicted in Figure 3. Most of the accidents occurred within the city, mainly on the Khulna-Jashore-Dhaka Highway, also known as N7 (National Highway 7). Some accidents happened on the Khulna City Bypass Road, also known as N709. There was also a tendency for accidents on connecting roads because of narrowness, traffic congestion within city roads, a lack of sidewalks, and public transportation.

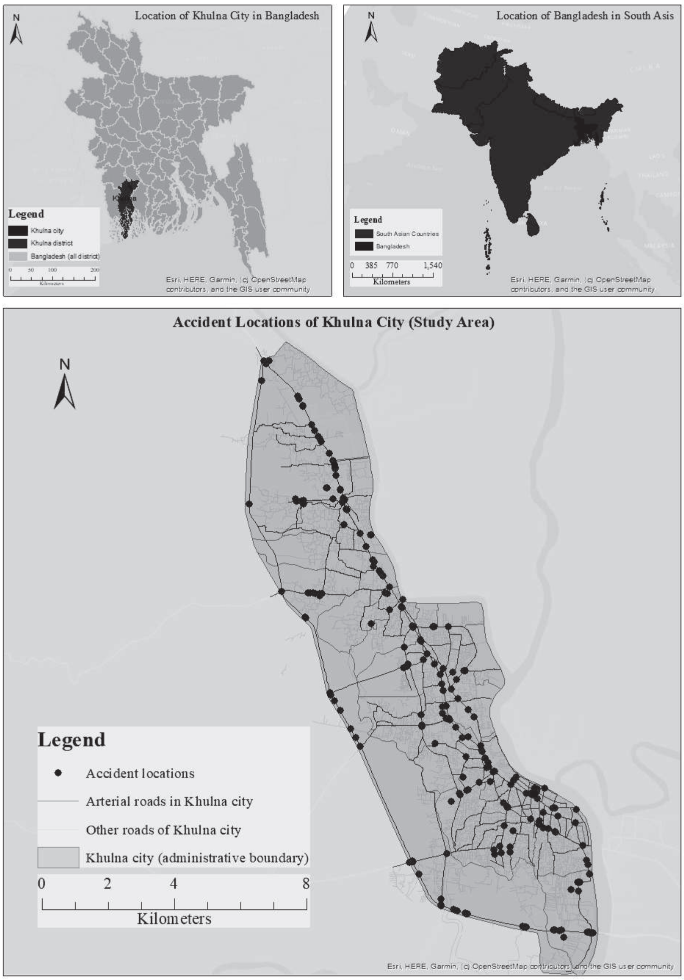

Figure 3: Location of road-traffic accident events in Khulna city (2010-2019)
Source: Authors, 2021

4.1 Variable selection

Data collinearity, cell frequency for categorical variables with the dependent variable, and likelihood ratio test for testing the significance of explanatory variables are analyzed and interpreted for selecting the explanatory variables for final binomial (or binary) logistic regression. Collinearity describes whether variables are highly correlated; cell frequency for categorical variables, with the dependent variable; and at last likelihood ratio test with a "p" value for testing the significance of predictor variables to predict accident severity significantly. After these steps, the final variables are found. Then, these variables are used in the model to predict the accident risk or severity through different explanatory variables.

4.1.1 Collinearity

The Variance Inflation Factor, or VIF, is a robust method that shows the collinearity of independent variables (Daoud, 2017). Collinearity is a problem of data, not a problem of the model. It occurs when two variables have a strong correlation (Daoud, 2017; Greene, 2003). The VIF is the reciprocal of tolerance, and there are different cutoff values for tolerance or VIF (Daoud, 2017; Miles, 2014). One popular tolerance cutoff value for tolerance is 0.2. The tolerance cutoff value needs to be greater than 0.2, so if the tolerance is less than 0.2, that will show multicollinearity (Ringle, Wende, & Becker, 2015). So, a VIF of less than five (05) is needed to enter the regression model, and greater than five (05) is problematic.

Table 2: Collinearity statistics

Independent variables	Collinearity statistics	
	Tolerance	VIF
Type of vehicles	0.922	1.084
Vehicle ownership	0.933	1.072
Velocity of vehicle	0.877	1.140
Accident time	0.958	1.044
Location of accident	0.968	1.033
Number of fatality	0.757	1.320
Number of injury	0.556	1.798
Type of injury	0.538	1.858
Type of collision	0.954	1.048
Reporting status of accident	0.699	1.431

Source: Authors, 2021

Table 2 shows the collinearity statistics of independent variables, and for every variable, the VIF is less than five (05), or the tolerance is more significant than 0.2. So, according to tolerance, there isn't any problem with collinearity for any variable. So, all these variables can be used for the regression model if needed.

4.1.2 Comparison of cell frequency for categorical variables with the dependent variable

For cell count, there is a widely used rule of thumb. A low cell count shows insufficient subjects to generalize any statistics (Garson, 2012). So, no cell in factor space should be 0 in the cross-tabulation, and 80% of the cells should be greater than five (05) (Garson, 2012; McHugh, 2013). So, a minimum cell frequency of five among categorical variables with the dependent variable is needed to run a multinomial regression model. Table 3 shows an overview of the condition of cell frequency for categorical variables with the dependent variable (accident severity: either fatal or non-fatal) found through cross-tabulation.

Table 3: Cell frequency of categorical variables compared to dependent variable

Independent variables (categorical)	Cell frequency
Accident time	No cell has a cell frequency of less than 5
Velocity of vehicle	No cell has a cell frequency of less than 5
Location of accident	No cell has a cell frequency of less than 5
Reporting status of accident	Five (5) factor spaces have 0 cell count
Type of vehicle	No cell has a cell frequency of less than 5
Vehicle ownership	No cell has a cell frequency of less than 5
Type of injury	No cell has a cell frequency of less than 5
Type of collision	No cell has a cell frequency of less than 5

Source: Authors, 2022

Except for reporting the status of the accident, all the variables have a minimum cell frequency of five compared to the dependent variable accident severity. Compared to the dependent variable (accident severity), the reported status of an accident has five-factor spaces with zero cell count. So, we have to reject the reported status of an accident according to expected cell frequency.

4.1.3 Likelihood ratio test and "p" value

For this research, the null hypothesis states that the risk or severity of road traffic accidents does not relate to the selected independent variables or the values of the independent variables. The alternative hypothesis is the hypothesis of significance. It can be expressed as the significant differences in how this model's explanatory variables affect different vehicles. A p-value is a probability that shows whether to accept or reject the null hypothesis (Dahiru, 2008). If the p-value or significance value is less than the significance level, the null hypothesis is rejected; the null hypothesis is accepted if the p-value is more significant than the significance level. Table 4 displays the likelihood ratio tests for the selected independent variables for the dependent variable accident severity. For indicating risk or severity of road traffic accident severity by the independent variables, the p-value would be 0.015, more diminutive than 0.10, to predict the dependent variable significantly.

Table 4: List of accident risk predictor independent variables

Variables	Likelihood ratio tests	
	Chi-square	Sig.
Number of injuries	7.705	0.103*
Number of fatalities	7.830	0.098*
Velocity of vehicles	12.305	0.015**
Injury type	11.339	0.183
Time of accident	48.211	0.000***
Location of accident	27.185	0.296
Collision type	33.009	0.007***
Types of vehicle	8.417	0.077*
Vehicle ownership	6.478	0.011***

** Significant at 10% level, ** Significant at 5% level, *** Significant at 1% level.*
Source: Authors, 2022

Table 4 shows that all variables are significant except the injury type and location of the accident. So, the injury type and location of the accident have been rejected.

4.2 Modeling the Risk Factors According to Different Vehicular Types

Severity or risk assessment is the primary aim of this research. Regression models are used to assess risk from the accident data because the regression models can predict the severity, impact, risk, or probability of impact or risk. Accident or crash data analysis is a common type of analysis done through logistic regression models. The logistic regression models are compatible with the outcome as probability, impact, the relationship among variables, or even predicting the riskier level among different levels in a variable (Murata et al., 2015; Garson, 2014). In this research, the binomial logistic regression model has been generated to explain the severity or risk of road traffic accident events. The accident severity is considered as the dependent variable. The severity shows two different categories; fatal and non-fatal accidents. For these two dependent categories of the dependent variable, the severity of accidents has been preferred to predict. So, the relation between different modes and accident severity can be indicated from the output.

Binary logistic regression allows only two categories for the dependent variable. It uses maximum likelihood ratio estimation to predict the probability of outcomes of happening one particular event for the possibility of not occurring that event. If k= number of predictor variables in the model; β_0= interception at y-axis; β_1= line gradient; β_k= regression coefficient of X_k; X_1, X_2, X_3… X_k = predictor variables; and e= random error, then according to Al-Ghamdi (2002) and Berenson et al. (2012), the final equation for binary logit is:

$$P = \frac{e^{\beta_0+\beta_1 X_{1i}+\beta_2 X_{2i}+\beta_3 X_{3i}+\beta_k X_{ki}+e}}{1+ e^{\beta_0+\beta_1 X_{1i}+\beta_2 X_{2i}+\beta_3 X_{3i}+\beta_k X_{ki}+e}} \quad \text{...(i)}$$

The formulation of this equation is described in the method selection portion of the chapter methodology. According to equation (i), the probability of a happening fatal accident is:

$$P(fatal)=\frac{e^{\beta_0+\beta_1(\text{Number of Injury})+\beta_2(\text{Number of Fatality})+\beta_3(\text{Velocity of Vehicles})+\beta_4(\text{Accident Time})+\beta_5(\text{Collision Type})+\beta_6(\text{Types of Vehicle})+\beta_7(\text{Vehicle Ownership})+e}}{1+e^{\beta_0+\beta_1(\text{Number of Injury})+\beta_2(\text{Number of Fatality})+\beta_3(\text{Velocity of Vehicles})+\beta_4(\text{Accident Time})+\beta_5(\text{Collision Type})+\beta_6(\text{Types of Vehicle})+\beta_7(\text{Vehicle Ownership})+e}} \quad ...(ii)$$

Source: Authors, 2021

The probability of happening non-fatal accident is:

$$P(nonfatal)=1-\frac{e^{\beta_0+\beta_1(\text{Number of Injury})+\beta_2(\text{Number of Fatality})+\beta_3(\text{Velocity of Vehicles})+\beta_4(\text{Accident Time})+\beta_5(\text{Collision Type})+\beta_6(\text{Types of Vehicle})+\beta_7(\text{Vehicle Ownership})+e}}{1+e^{\beta_0+\beta_1(\text{Number of Injury})+\beta_2(\text{Number of Fatality})+\beta_3(\text{Velocity of Vehicles})+\beta_4(\text{Accident Time})+\beta_5(\text{Collision Type})+\beta_6(\text{Types of Vehicle})+\beta_7(\text{Vehicle Ownership})+e}} \quad ...(iii)$$

Source: Authors, 2021

4.3 Model Interpretation

According to the likelihood ratio test, the last model is significant (0.000***) at the 99.99% confidence interval. So, this model is appropriate for binomial logistic regression, and the independent variables influence the accident's severity. According to McFadden (1977), a good value of pseudo-R-square for a suitable model fit ranges between 0.2 and 0.4, and the value for this study is 0.420. According to McFadden's referred value of R-square, the model fits the data well.

The risk or severity of a road traffic accident is determined by the prevailing circumstances and conditions of the surrounding environment at the time of the accident. This study compared various explanatory variables to the indicators that assess the risk of road traffic accidents. Using a binomial logistic regression model, the authors investigated how these indicators affected the severity of a road accident compared to other explanatory variables. The authors organized and interpreted the model to explain the effects and probabilities of these indicators by describing the severity of road traffic accident events.

Table 5: Binary logistic model for accident severity

Indicators	Category of Indicators	Coefficient β	S.E.	Odds Ratio Exp (B)	95% Confidence Interval for EXP(β)	
					Lower	Upper
Number of injuries		0.693	0.133	2.000	0.383	0.686
Number of fatalities		0.735	0.134	2.085	0.582	0.721
Velocity of vehicles	Above 40km/hour	1.430	0.289	4.180	2.374	7.359
Accident time	Morning rush hours	0.182	0.505	1.200	0.446	3.227
	Morning working hours	-0.247	0.458	0.782	0.318	1.919
	Afternoon working hours	-0.687	0.447	0.503	0.210	1.208
	Afternoon rush hours	-0.442	0.488	0.643	0.247	1.673
	Night time	-0.336	0.502	0.714	0.267	1.912

Table 5: Binary logistic model for accident severity (continued)

Indicators	Category of Indicators	Coefficient β	S.E.	Odds Ratio Exp (B)	95% Confidence Interval for EXP(β)	
					Lower	Upper
Type of collision	Rear-end collision	-0.277	0.577	0.758	0.244	2.349
	High-speed collision	0.123	0.466	1.131	0.454	2.817
	Head-on collision	-0.722	0.567	0.486	0.160	1.475
	Side-swipe collision	-0.731	0.558	0.481	0.161	1.437
Vehicle ownership	Public vehicle	0.680	0.267	1.973	1.169	3.330
Types of vehicles	Motorcycle	-0.512	0.369	0.599	0.291	1.237
	Pickup truck	0.315	0.439	1.370	0.579	3.240
	Private car	-0.295	0.426	0.744	0.323	1.716
	Truck	0.478	0.374	1.612	0.775	3.355

Dependent Variable: Accident Severity (Fatal=1, Non-fatal=0)
Source: Authors, 2022
[In the model, the first category of each independent variable is used as a reference category, which is not shown in the table. The reference category is used to compare the risk prediction of the table's remaining categories.]

According to Table 5, the probability of a fatal accident increases by 0.693 and 0.735 times, respectively, based on the number of injuries and fatalities. The confidence interval for the slope, or value 0.693, ranges from 0.383 to 0.686 for the number of injuries, showing that if an injury occurs in an accident, the probability of a fatal accident is increased between 0.383 and 0.686 times. However, if a fatality occurs, the accident must be fatal. According to vehicle velocity, there is a 1.430 times greater probability of a deadly accident for vehicles traveling at speeds greater than 40 km/hour than vehicles traveling at speeds less than 40 km/hour. The confidence interval for the slope, or β value 1.430, ranges from 2.374 to 7.359, showing that if an accident occurs at speeds greater than 40km/h, the likelihood of a fatal accident increases between 2.374 7.359 times. According to the accident time, the reference category is midnight to down. So, based on the confidence interval, it can be stated that if an accident occurs during morning rush hours, the probability of a fatal accident ranges from 0.446 to 3.227 times greater than at midnight to down.

Similarly, the likelihood of a deadly accident occurring during morning working hours, afternoon working hours, afternoon rush hours, and night time ranges from (0.318 to 1.919), (0.210 to 1.208), (0.247 to 1.673), and (0.267 to 1.912), respectively. The road-cross collision is the reference category in terms of collision type. So, based on the confidence interval, it can be stated that if an accident occurs via rear-end collision, the probability of being a fatal accident ranges from 0.244 to 2.349 times greater than a road-cross collision. Similarly, the likelihood of a deadly accident occurring in a high-speed collision, head-on collision, and side-swipe collision ranges from (0.454 to 2.817), (0.160 to 1.475), and (0.161 to 1.437) times, respectively. When comparing private vs. public vehicles, public vehicles have a 0.680 times higher probability of being involved in a fatal accident than personal vehicles. The confidence interval for the slope, or β value 0.680, ranges from 1.169 to 3.330 times, showing that if an accident occurs involving a public vehicle, the probability of a fatal accident is higher between 1.169 and 3.330 times. The bus is the reference category in terms of vehicle type. So, based on the confidence interval, it can be stated that if a motorcycle accident occurs, the probability of a fatal accident ranges from (0.291 to 1.237) times greater than that of a bus accident. Similarly, the likelihood of a deadly accident occurring in a pickup truck, private car, and truck ranges from (0.579 to 3.240), (0.323 to 1.716), and (0.775 to 3.355) times, respectively.

However, these are the interpretations of accident events of being fatal or non-fatal compared to the coefficient of β. However, the explanatory variables' odds ratio or exp(β) can describe the odds of a fatal accident. The odds ratio interprets the percentage of the probability of being in a fatal accident versus the likelihood of being in a non-fatal accident. Table 7 also expresses the odds ratio or exp(β) with the coefficient of β of the predictors in the entire model. The odds ratio of the number of injuries is 2.000, which shows the occurrence of an accident 2.000 times higher odds of being fatal when an injury occurs. The odds ratio of the vehicle's velocity above 40km/hour is 4.180, which shows the occurrence of an accident above 40km/hour vehicular speed puts it 4.180 times higher odds of being an accident fatal. Morning rush hours, morning working hours, afternoon working hours, afternoon rush hours, and night time have odds ratios of 1.200, 0.782, 0.503, 0.643, and 0.714, respectively, showing that an accident occurring during morning rush hours, morning working hours, afternoon working hours, afternoon rush hours, and night time has 1.200, 0.782, 0.503, 0.643, and 0.714 times higher odds of being a fatal accident. The odds ratios of a rear-end collision, a high-speed collision, a head-on collision, and a side-swipe collision are 0.758, 1.131, 0.486, and 0.481, respectively, showing the occurrence of an accident. However, a rear-end collision, a high-speed collision, a head-on collision, and a side-swipe collision have 0.758, 1.131, 0.486, and 0.481 times. The odds ratio of a public vehicle is 1.973, showing that the occurrence of an accident involving a public vehicle increases the likelihood of a fatal accident by 1.973 times. The odds ratios of a motorcycle, pickup truck, private car, and truck are 0.599, 1.370, 0.744, and 1.612, respectively, showing that the occurrence of an accident by motorcycle, pickup truck, private car, and truck has 0.599, 1.370, 0.744, and 1.612 times higher odds of being a fatal accident.

5. DISCUSSIONS OF RESULTS

This research targets the factors affecting road traffic accident severity compared to different explanatory variables. This research has taken seven significant indicators or predictor variables affecting the road traffic accident severity. The explanation and description of the results found from the final analysis have been discussed below.

5.1 Factors Affecting Road Cccidents

This study has identified seven significant determinants to predict the accident severity and the risk or impact of accidents compared to different transport modes. However, the finding of this research is that the risk of road accidents increases if the number of injuries increases. According to Zajac and Ivan (2003), an increasing number of injuries influence the severity of road traffic accidents. The number of injuries and the risk of road accidents have a positive and growing relationship with road traffic accident severity. The probable explanation for the increased risk might be the carelessness of drivers during driving, less experienced drivers, craggy road conditions, terrible vehicle conditions, or the high speed of vehicles. Because of minor professional and driver's negligence, the driver might not drive proficiently in poor road conditions or lose the balance of their vehicles. The number of fatalities or accidents related to a fatality describes the severity of accident events. The explanation might be the safety and security of vehicles, the carelessness of drivers, and less skilled drivers.

When vulnerable humans are associated with the severity of an accident, the consequences of errors can be dangerous. Khulna city is consistent with Garder's (2004) study, which explains that low-speed locations have fewer risks than high-speed locations. In Khulna, the risk of an accident has increased with increasing velocity. The most likely explanation is that as the vehicle's acceleration increased, the vehicle's balance at lower speeds was compromised. As a result, road accidents have occurred as higher speeds have disrupted drivers' concentration, even if the surrounding circumstances have changed slightly.

According to the time of the accident in this study, morning rush hours and morning working hours have a higher risk of accident severity than afternoon rush hours and afternoon working hours. According to Awal (2013), accidents in the morning hours are more severe than in the afternoon. This could be because people were rushing to work in the morning, and the roads in Khulna were much busier than in the afternoon. We have found that night time traffic accidents are more severe than afternoon traffic accidents. The explanations might be the safety and lighting situation (only some significant portions, like the CBD and some intersections, of the study area, have good street lighting conditions) and the elements of urban design (for example, permeability) are in poor condition. So, the severity of road traffic is more significant at night than afternoon working and rush hours.

The severity of road traffic accidents increases with rear-end and high-speed collisions. The most likely causes of these two types of collisions are driver carelessness, and sometimes, unconsciousness while parking or turning their vehicles. These collisions pose a high risk of accident events for heavy vehicles (such as buses or trucks). High-speed collisions have a higher number of accident events; the high speed of vehicles may cause vehicle loss of balance.

According to the final binomial logistic regression model, the accident severity increases for different vehicle types in this study. In their research, George, Athanasios, and George (2017) analyze and explain the severity of road traffic accident events for various types of vehicles. Moeinaddini et al. (2015) and Porcu, Olivo, Maternini, and Barabino (2020) investigate the same kind of research. Our country's accident severity has different assumptions and variability because road traffic conditions, circumstances, and safety measures are much worse than developed and developing countries. In Khulna, the road traffic condition and safety measures of the road and the vehicles are deplorable. According to Moeinaddini et al. (2015), motorcycles are associated with more road accident deaths, and motorized vehicles in urban areas may cause more conflicts. More traffic flow by various types of non-motorized transport, using the same route for motorized and non-motorized vehicles, failure to follow traffic rules, poor safety measures, poor parking facilities, and on-site and off-site parking management all contribute to the situation becoming more severe and accident-prone. In this research, public vehicle accidents have been found to be more potent than those involving private vehicles. According to the condition of public and private vehicles, Moeinaddini et al. (2015) found an opposite situation. Moeinaddini et al. (2015) found that the percentage of journeys to work by public transportation is negatively associated with road accident fatalities, and cities with more journeys by public transportation mode have fewer fatalities. They also found that the overall crash risk for public transportation is low. However, Singh and Misra (2004) found in Patna, India, that public transport is insufficient, inefficient, and poorly planned; as a result, the accident severity in Patna is higher. According to Oluwole, Rani, and Rohani (2015), and Porcu et al. (2020), public vehicles had higher accident severity. The reasons for this could include the developed versus underdeveloped or developing countries and the road traffic accident situations in these countries. Moeinaddini et al. (2015) studied accident severity in European or developed cities. They found developed safety measures for their public vehicles, so the severity of road traffic accidents has decreased. Oluwole et al. (2015), Singh and Misra (2004), and Porcu et al. (2020) studied accident severity in developing cities, and they found that developing or underdeveloped cities or countries have poor road traffic safety. Hence, road traffic accidents are more severe in public vehicles. Aligning to underdeveloped or developing cities, public vehicles have a higher severity of road traffic accident events than private vehicles in Khulna because safety measures and traffic management procedures are inadequate.

6. CONCLUSION AND RECOMMENDATIONS

This study finds the factors affecting road traffic accidents and the severity of accidents compared to different transport modes. Predicting the relationship between vehicle and accident rate means the risk of an accident compared to other transport modes. The findings show that seven variables (number of injuries, number of fatalities, vehicle velocity, time of accident, collision type, vehicle type, and vehicle ownership) significantly impact accident severity of road traffic accident occurrences. Among these factors are environmental factors, human factors, and vehicle factors. Human factors include vehicle ownership, number of injuries, and number of deaths. The vehicle's velocity, vehicle type, and collision type are vehicle factors; the time of the accident is the environment-related factor. Based on the findings and discussion, the danger of road accidents in Khulna city increases with each increase in the number of injuries, fatality, the velocity of the vehicle, time of the accident, collision type, and vehicle ownership. Another finding of this research to different vehicles is that the risk of a road accident, from highest to lowest, is the truck, pickup truck, private car, and motorcycle, respectably compared to a bus.

The data collection process isn't updated and changed regularly, and the data collection and management process is inefficient. The Traffic Branch of the Deputy Police Commissioner of Khulna Metropolitan Police has the speedometer technology, but they didn't use it all the time and all the places. The Traffic Branch of Khulna Metropolitan Police should manage it. Then the data will measure the expected road accident outcomes significantly through different levels of vehicular speed. Despite these limitations, the results or findings found in this study have significant implications for safety measures, interventions, and policy formulations. The number of private vehicles is much higher inside Khulna city. As we have found that the severity of public vehicles is more significant than personal vehicles in Khulna city and according to Hossain et al. (2005), in Khulna, rickshaws and other non-motorized transport accounts for 60% of the overall traffic flow, so to improve the safety, security and reducing the severity of public vehicles, the private and non-motorized vehicles should be prevented and managed either through initiating different routes for them or reducing the number of them through restrictions. General used to go to the working place in morning rush hours, and they also used to go to the home in afternoon rush hours, in these hours the traffic remains most. Private and non-motorized vehicles should be prevented, and people should use only public vehicles in rush hours, and for working hours, people can use personal vehicles inside the city. So, inside the city the use of public vehicles should be increased through introducing more bus routes and the use of private vehicles should be decreased. Extensive and significant research relevant to this study and understanding can find more prominent and practical recommendations, where this study can be a good door for future research options.

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