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Exploring Drivers Age Influence on Crash Indicators: Perception Based Studies In A Developing Country

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ABSTRACT: Road traffic accidents (RTAs) are a significant concern in developing countries, such as Bangladesh, resulting in the loss of life or property. To minimize those valuable losses, it's necessary to gain deeper insights into the associated factors and circumstances of these accidents. Although extensive work has been done on RTA in developed countries, developing countries lag far behind. This study was conducted to bridge the literature gap, identify associated factors and assist authorities in making informed decisions. The main purpose of this research is to identify the age group (young, middle-aged and old) that is most frequently involved in road crashes and the circumstances (crash factors) that influence the crash occurrence of specific age groups from the perspective of a developing country. No research has been conducted to investigate the associations between crash scenarios and driver age groups in a developing country context. The study utilized a Driver Behavioural Questionnaire (DBQ) which had 3000 participants from Rajshahi, Bangladesh. To analyse the relationship between age and crash involvement, this research utilized three models: Poisson Regression, Gamma Regression and Ordered Probit Regression from where the Ordered Probit Model showed the best balance between the model's complexity and performance. The analysis has revealed that factors such as vehicle speed, lighting conditions, driver occupation, possession of a driving license, improper lane change and driving disability have significant influences on determining age groups involved in crashes. Middle-aged male drivers are more likely to engage in aggressive driving, resulting in higher crash involvement rates. Maintaining smooth driving and careful lane changes greatly decreases crashes. In contrast, sudden speed reductions, disabilities, and inattentiveness during lane changes have led to frequent accidents among middle-aged drivers.

KEYWORDS: Crash outcome; Drivers Age; Drivers Behaviour; Traffic Crash; Developing Country.

1 INTRODUCTION

Globally, Road Traffic Accidents (RTAs) are widely acknowledged as the primary cause of mortality. People die 5% of the time around the world because of injury, and a lot of those injuries are caused by vehicular crashes (Wang et al., 2009). In developing countries, road safety is seen as a major problem because vehicular crashes usually have devastating effects on people's lives and the economy (Bin Siraj et al., 2021; Kamruzzaman et al., 2014; yu et al., 2021). There is a disproportionate distribution of road crashes between developed and developing countries (Agrawal, 2017; Oginni et al., 2009). Two-thirds or more of all injuries worldwide occur in developing countries (Fatmi et al., 2007). Bangladesh has a severe problem regarding this because there are a lot more deaths from vehicular accidents compared to the population and vehicles on the roads (Ahmed et al., 2014).

This study's research area was Rajshahi, a significant divisional metropolitan city in Bangladesh. The road traffic fatality rate in this city has experienced a substantial increase in recent years. Between 2018 and 2020, 94 accidents were recorded, resulting in 45 fatalities and 126 injuries (Hasan et al., 2021). In 2023, a staggering number of 5024 fatalities were recorded in road traffic accidents all over Bangladesh. 74 accidents occurred alone in December in the Rajshahi division (*BRTA*, 2024). Global statistics prove the fact that approximately eight people lose their lives every day in road accidents (Bhuiyan et al., 2022). However, the figure is higher than that mentioned number, as not all individuals who experience injuries make a general diary at the police station. The rate of road crashes resulting in fatalities and injuries is increasing in developing countries, whereas the rate is decreasing in developed countries (Berhanu et al., 2023; Banik et al., 2026). In contrast to the extensive research conducted in developed countries (Banik et al., 2026; Banik et al., 2026) and the alarming number of crashes, there has been a dearth of research on the factors contributing to crash outcomes in Bangladesh, particularly in Rajshahi (Pervaz et al., 2022).

Drivers' behavior and demographic characteristics significantly impact road crashes. A notable amount of research has been conducted in developed countries using statistical analysis to evaluate drivers' behaviour concerning traffic safety and other relevant factors. These studies included factors such as the driver's age, gender, occupation, license, weather conditions, lighting conditions, etc. (Martinussen et al., 2013; Zhao et al., 2012). These studies have a huge impact on road safety, offering hope for a safer future on the roads. It is necessary to understand driver behaviour and the associated factors that contribute to the crashes in order to create effective road safety initiatives.

Dahlen et al. (2012) found that driving impulsively increases the likelihood of crash severity. The study found an association with anger to lower driving performance and increased crash risk as anger impairs the judgment and coordination of the drivers (Dahlen et al., 2012). Extensive work has been done on this topic in developed countries, creating a gap in developing countries such as Bangladesh. To evaluate the factors influencing traffic accidents in Bangladesh. Shaik

et al (2020) utilized negative binomial, gamma regression, and Poisson regression. The study found that loss of control, buses, trucks and junctions are the contributing factors in road crashes (Shaik & Hossain, 2020). Another work by S Hossain et al. (2022) found driving the wrong way, not having speed limit signs, and not having enough street lights are the main risk factors that add to the likelihood of fatalities in traffic accidents (Hossain et al., 2022).

A significant amount of research has yet to be conducted in Rajshahi. Mahmud H et al. showed that certain places are more accident-prone, and trucks and buses are the factors that contribute to crash incidents (Mamun et al., 2015). Hasan et al. (2021) conducted a survey using a questionnaire that had data about vehicular conditions, road characteristics, and demographic measures for road users. Descriptive analysis was conducted to understand Rajshahi's current accident scenario (Hasan et al., 2021). A study by A. H. Zilan et al. (2021) analysed the contributing factors of crash severity. This study included analysis of variance, chi-square test and odds ratios. Findings showed that influential factors were speeding, driving with poor vision, poorly maintained signals, and faulty lane links (Zilan et al., 2021). Previous studies on traffic safety have mainly focused on how various factors affect crash severity, identifying which incidents result in more severe crashes and the factors that contribute to this increase. A study by D. McCarty et al. (2024) used machine learning algorithms to assess the effects of demographic factors on crash frequency in the UK. The analysis revealed that demographic factors significantly influence crashes (McCarty & Kim, 2024). A study in the Czech Republic analysed the age group most frequently involved in crashes and the factors that increased the likelihood of involvement in crashes. They identified inattention while driving as the primary cause of accidents across all age groups, while the oldest group being more prone to accidents (Řezníček & Kovač, 2025). Table 1 provides more details about the earlier study concerning road crashes. However, the relationship between crash characteristics and driver age groups presents an equally important yet less explored perspective. Literature still lacks clarity on which age group, Young (<30 years), Middle (30-50 years), or Old (50+ years) is more susceptible to road crashes in Bangladesh. This research adopts a different perspective by treating driver age groups as the dependent variable, examining the relationship between various crash circumstances and distinct age cohorts in Bangladesh, a perspective that has not been explored to this extent in developing countries. The age group interval used in this study was selected to maintain consistency with the existing Bangladesh Road Safety Research (Iqra et al., 2022).

In this study, data were collected through a survey using the Driver Behavioural Questionnaire (DBQ), previously used in developed countries (Chen & Chen, 2020). This questionnaire included demographic characteristics of drivers and potential factors contributing to crashes, such as vehicle type, license type, gender, weather, lighting conditions, collision type, accident severity, journey purpose, major cause of the accident, speed, and others. The collected data were analysed using the three models. The Ordered Probit Regression Model, the Poisson Regression Model, and the Gamma Regression Model, where the driver's age group was the dependent variable, and the rest of the features were independent. The study includes the following key objectives:

1. To compare and identify appropriate statistical models for analysing the data obtained from DBQ.
2. To determine the age group most involved in road crashes in a developing country.
3. To identify the factors that influence the engagement of a particular age demographic in road crashes.

Study	City, Country	Developed or developing	Method	Industrial/not
(Shaik & Hossain, 2020)	Khulna, Bangladesh	Developing	Negative binomial, gamma regression, and Poisson regression model	Industrial
(M.-M. Chen & Chen, 2020)	Taiwan	Developed	Logistic regression (LR), classification and regression tree (CART), and random forest (RF)	Both
(A. Hossain et al., 2024)	Louisiana, USA	Developed	Binary logit model	Industrial
(Siddique, 2018)	Bangladesh	Developing	Ordered Probit Model	Both
(Thierry et al., 2023)	Bangladesh	Developing	Local Record Keeper (LRK)	No
(Akin, 2011)	Michigan, USA	Developed	Negative binomial and Poisson regression model	Industrial
(S. Hossain et al., 2022)	Dhaka, Bangladesh	Developing	Probit model	Industrial
(M. Hossain & Faruque, 2019)	Bangladesh	Developing	Augmented Dickey-Fuller (ADF) test (a unit root test) and Philip Perron test	Both
(Kamruzzaman et al., 2014)	Dhaka, Bangladesh	Developing	Ordered Probit Model	Industrial
(Harrison et al., 2019)	Nigeria	Developing	Poisson regression, Generalized Poisson Regression, Negative Binomial Regression and Generalized Negative Binomial Regression	Both
(Zafri et al., 2020)	Dhaka, Bangladesh	Developing	Binary logistic regression	Industrial
(Salehian et al., 2023)	United Kingdom (UK)	Developed	Ordered Probit model	Industrial
(Sayed et al., 2022)	Egypt	Developing	Negative binomial models	Industrial
(Boufous et al., 2011)	New South Wales, Australia	Developed	Poisson regression model	Industrial
(Cardamone et al., 2014)	Italy	Developed	Stated Preferences (SP)	Both
(Thomas & Walton, 2008)	Wellington, New Zealand	Developed	Poisson regression model	Industrial
(Y. Chen et al., 2022)	China	Developed	Structural equation modeling (SEM)	Industrial
(Martinussen et al., 2013)	Denmark	Developed	Structural equation modeling (SEM)	Both

Table 1. Previous study summary

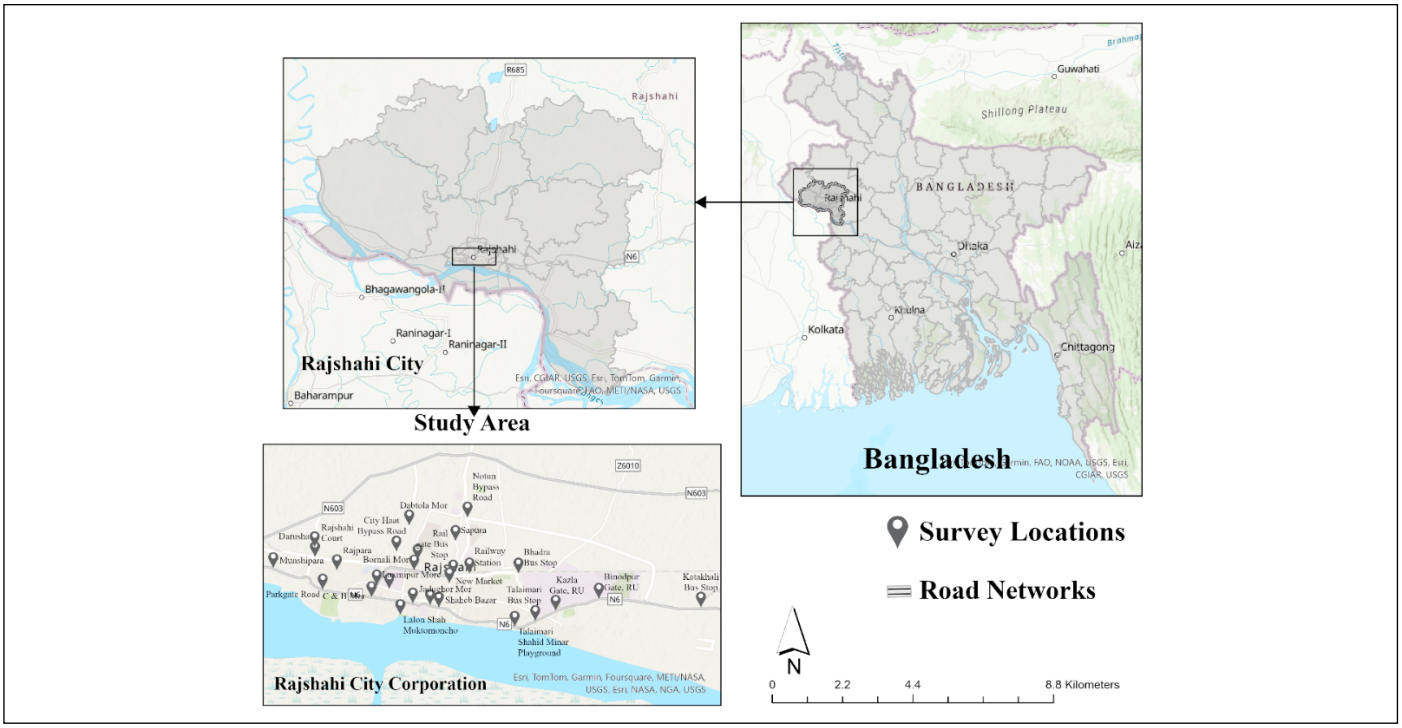


Figure 1. Locations of Study Area.

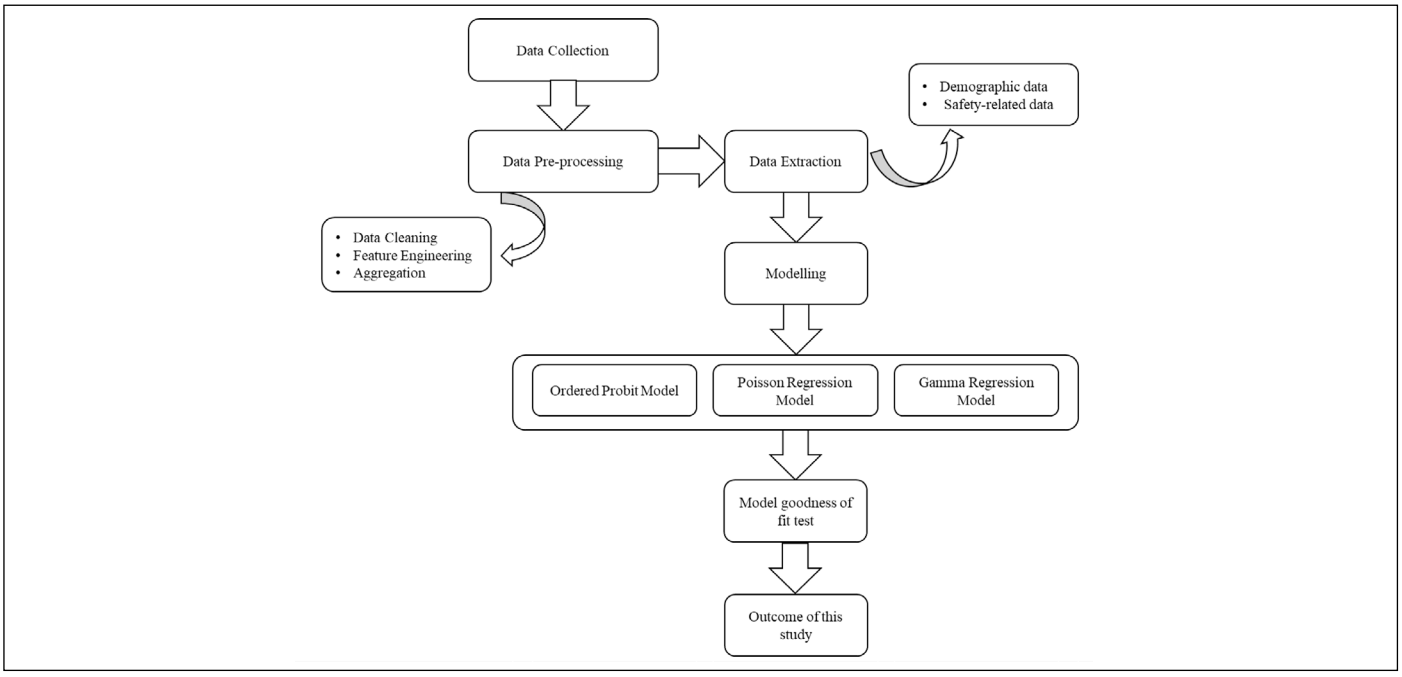


Figure 2. Study workflow

Following this introduction, the paper is structured as follows: Section 2 Methodology describes the overall structure of this study. Section 3 explains the data analysis, and Section 4 shows the results of different models. Section 5 discusses the outcomes and draws the conclusion.

2 METHODOLOGY

2.1 Data collection

The data was collected from the Driver Behavioural Questionnaire (DBQ) survey, as individual interviews were carried out with a total of 3,000 drivers of various profiles at 27 selected locations ("Figure 1") in the Rajshahi City Corporation (RCC), Rajshahi, Bangladesh. Geographically, the Rajshahi City Corporation (RCC) is situated between 24°20'and 24°24'north latitudes and 88°32'to 88°40'east longitudes. This urban area comprises 96.72 Km^2 with around 0.85 million residents (Ahmad et al., 2024).

The dataset has a wide range of information, which includes drivers' gender and age, occupation, license status, accident severity, type of vehicle, journey purpose, accident causes, weather conditions, vehicle crash position, location on roadway, and speed of the vehicle. Following the data collection, the pre-processing stage involved data cleaning, feature engineering and aggregating in preparation for the analysis. Relevant demographic and safety-related data were extracted to build three statistical models: The Ordered Probit Model, the Poisson Regression Model, and the Gamma Regression Model. Each of the three models analyses different aspects. A correlation analysis was conducted to elucidate the existing relationships between these variables.

The models were compared based on goodness-of-fit statistics, including the scaled deviance per degree of freedom, the Pearson Chi-Square value per degree of freedom as well as the log-likelihood, AIC and BIC, to determine the best model. "Figure 2" provides a general overview of the data analysis process, from data collection to the study result.

2.2 Sample size

The sample size for the study was determined based on the population of the Rajshahi City Corporation (RCC) using Solvin's formula (Herath et al., 2023) as shown in Eq. (1),

$$(1)\quad n = \frac{N}{1+NE^2}$$

Here,
n = Sample size.
N = Population size (0.85 million=850000).
E = Error tolerance (in this study 95% confidence interval was chosen, indicating a margin of error of 5% or 0.05).

$$n = \frac{850000}{1+850000\times 0.05^2} = 399.81 \approx 400$$

Hence, while the minimum required sample size was 400 respondents, the study included a sample size of 3000 respondents.

2.3 Ordered Probit Model

In vehicle crash analysis, various regression models are used to handle or address various aspects within the data. When examining, there is use of ordered probit regression model particularly since the dependant variable is actually ordinal but not of equal intervals; this enables the comprehension of the impact of additional factors such as roads conditions or drivers' behaviour on the crash outcomes (Manu et al., 2012). Here is the equation for the Ordered Probit Model shown in Eq. (2),

$$(2)\quad y^* = \beta_0 + \beta_1 X_1 + \cdots . + \beta_i X_i + \varepsilon$$

Here,
y^* = Dependent variable that represents the underlying unobserved variable.
$\beta_0, \beta_1, \ldots, \beta_i$ = Regression coefficients that quantify the effect of the independent variables on the dependent variable
$X_1, X_2, \ldots, X_i$ = Independent variables
ε = Standard normal error

2.4 Poisson Regression Model

For instance, the Poisson distribution is suited to count variables and its regression form is applied in crash frequency studies at locations, such as intersections or road segments, to declare variables that i...nfluence the likelihood of crashes and are defined by volumes and Road design (Miaou & Lum, 1993). Here is the equation for the Poisson Regression Model shown in Eq. (3),

$$(3)\quad \log(\lambda) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots, + \beta_j X_j$$

Here,
λ = Poisson rate parameter, which represents the average number of occurrences of the event.
β_0 = Intercept term
$\beta_1, \beta_2, \ldots, \beta_j$ = Coefficients associated with the independent variables $X_1, X_2, \ldots, X_j$
$\log \lambda$ = Natural logarithm of λ

2.5 Gamma Regression Model

On the other hand, the gamma regression model is used for continuous positively skewed data, including the cost or number of days that car-owners lose when their vehicles are to be repaired after an accident in order to establish their economic value and factors that determine the number of days or expense in case of an accident (Miaou & Lum, 1993). Here is the equation for the Gamma Regression Model shown in Eq. (4),

$$(4)\quad \log(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots, + \beta_k X_k$$

Here,
μ = Mean of the dependent variable
β_0 = Intercept term
$\beta_1, \beta_2, \ldots, \beta_k$ = Coefficients for the independent variables $X_1, X_2, \ldots, X_k$
$\log(\mu)$ = Natural logarithm of μ

2.6 Goodness of Fit Test

It is used most often to determine how well the observed data fits a given distribution. This test is a crucial identifier in statistics to help determine the compatibility of a model with specific data. Of all the tests of fit, the goodness of fit chi-square is probably the most frequently used. In this study, goodness of fit tests was conducted using the Chi-square test (Shaik & Hossain, 2020). This test is especially used when calculating data from a binomial or Poisson distribution, usually for simple random sampling of categorical variables.

2.7 Akaike's Information Criterion (AIC)

Akaike's Information Criterion (AIC) is one of the most popular estimators when choosing a model for statistical processing. Introduced by Hirotugu Akaike in 1974 (Akaike, 1974; Shaik & Hossain, 2020). A smaller value of AIC indicates a better fit of the models for the given data. The criterion originates from the balance that must be reached between the goodness of fit and model selection. Mathematically, AIC is defined as:

$$(5)\quad AIC = -2ln(maximum\ likelihood) + 2P$$
(Akaike, 1974; Shaik & Hossain, 2020)

Where P is the total number of parameters in the chosen model. A lower AIC value indicates a better-fitting model, making it a valuable tool for model comparison.

2.8 Bayesian Information Criterion (BIC)

The Bayesian Information Criterion (BIC) is another essential measure in model selection, especially for finite data samples. BIC is very similar to AIC, yet contains a penalty factor that is even more dependent on the number of parameters of the model in question (Omari-Sasu et al., 2016; Shaik & Hossain, 2020). This criterion is helpful in identifying the model that best describes the data in question and prevents over-fitting of data. Mathematically, BIC can be expressed as:

$$(6)\quad BIC = -2ln\,(maximum\ likelihood) + P\ ln(N)$$
(Omari-Sasu et al., 2016; Shaik & Hossain, 2020)

Where N is the number of observations in the data set. Like in the case of AIC, the BIC involves a lower number for a better model. BIC is a very effective statistic for comparing the suitability of regression models in explaining the data, which makes it possible to make a good choice in this matter.

Preliminary data analysis was conducted using Microsoft Excel to organize and explore the dataset. STATA software and Python programming languages were primarily utilized for comprehensive and detailed statistical analysis. ArcGIS software was employed to create visual representations of the study area.

3 DATA ANALYSIS

3.1 Demographic Characteristics

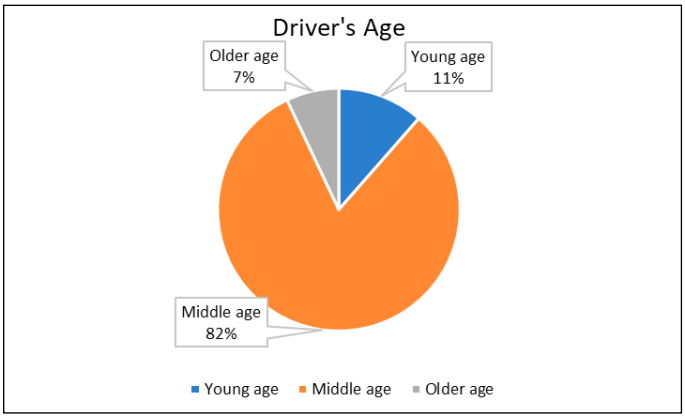


Figure 3. Crash distribution with respect to Driver's Age

The distribution of driver ages in crashes is depicted in "Figure 3". According to this study, 82% of the drivers involved in accidents were middle-aged (30-50 years old). Most drivers involved in crashes belonged to the middle-aged category, while a significant number of accident-prone drivers were young (<30 years old) % at 11%. On the other hand, older (50+ years old) drivers experienced the fewest accidents (7%). Middle-aged individuals are more likely to drive in this region, whether it's for an important trip or not. Elderly and younger individuals are not encouraged to drive for safety reasons and professional considerations. This is why the percentage of middle-aged people who drive is higher.

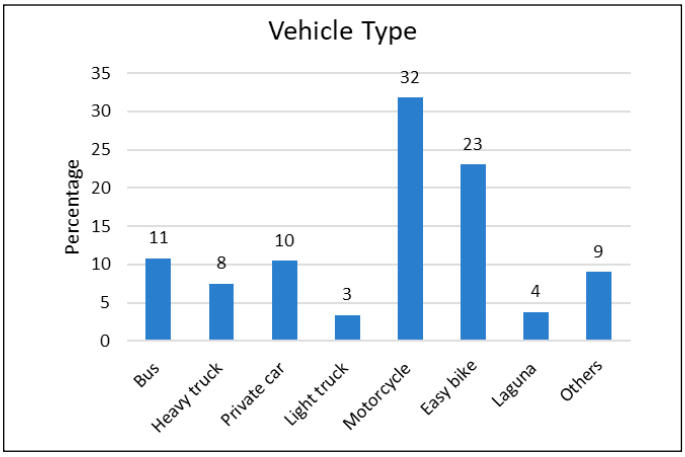


Figure 4. Crash distribution with respect to Vehicle Type

The study revealed that motorcycles accounted for nearly 32% of crashes ("Figure 4"). This can be attributed to the widespread use of motorcycles for daily commutes due to its cost-effectiveness. Auto rickshaws, commonly known as "easy bikes," were the second most involved vehicle in crashes, accounting for 23% of the total. Buses and private cars were also frequently involved in crashes, with percentages of 11% and 10%, respectively. The high involvement of buses can be attributed to their widespread use as public transportation, while the increasing ownership of private cars has contributed to their alarming involvement in accidents. Heavy and light trucks had lower involvement, accounting for 8% and 3% of the crashes, respectively. Additionally, 4% of the crashes involved lagunas, a modified pickup truck that is a small human-hauler vehicle typically used for short-distance public transport, especially outside major cities.

In "Figure 5" the percentage of drivers involved in accidents is depicted. Most were professional drivers, accounting for 65% of the total. Additionally, 14% of the drivers involved in accidents were job holders, while another 14% were students. Given that many people drive as part of their job, it is unsurprising that many drivers are involved in accidents. Moreover, students and job holders often use their vehicles for commuting. Only 2% of the drivers involved in accidents were found to be jobless.

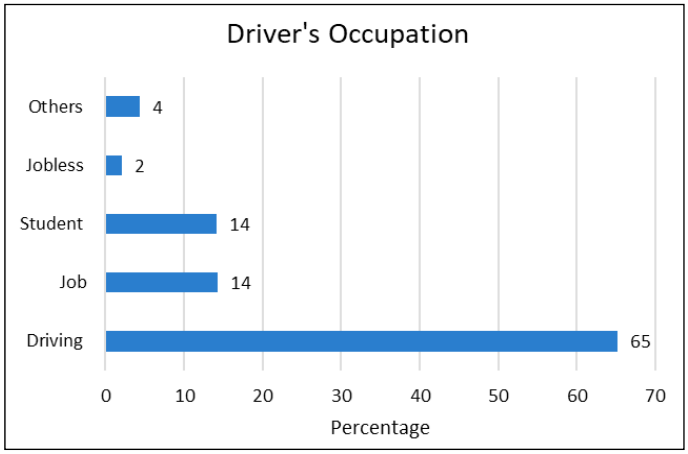


Figure 5 Crash distribution with respect to Driver's Occupation

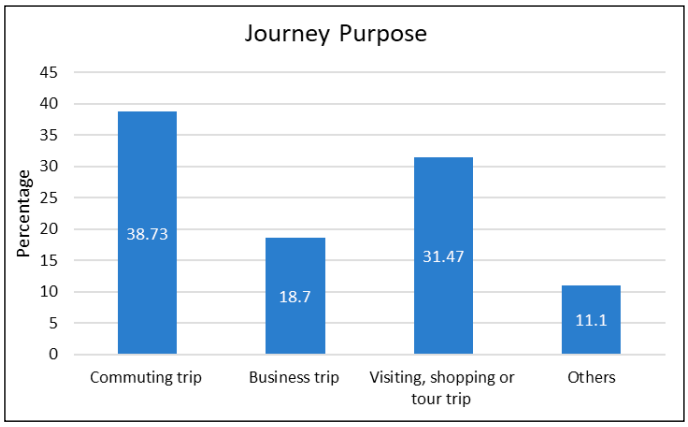


Figure 6 Crash Distribution with Respect to Journey Purpose

In "Figure 6", the percentage of trips for different journey purposes at the time of accidents is depicted. The highest number of accidents occurred during commuting, accounting for 38.73%. This can be attributed to the high population of Bangladesh, leading to many people using vehicles for commuting. Following that, 31.47% of accidents happened during shopping trips or visits/tours, as people frequently engage in these activities. Additionally, a notable number of crashes, 18.70%, occurred during business trips.

3.2 Safety Related Data

The crash factors extracted from the questionnaire are shown in "Table 2", highlighting various factors influencing road traffic accidents, such as severity, driver demographics, vehicle types and the conditions under which accidents occur. Accidents were categorized by crash severity, minor accidents at 41.73%, major at 38.23%, and fatal accidents at 20.03%. The highest percentage of accidents resulted from minor incidents, primarily from motorcycle accidents at 31.80%, while 23.13% of accidents were due to easy-bike crashes. The major cause of these accidents was improper lane change. Around 21.73% of accidents took place for that reason. 19.43% of accidents are caused by failures to keep a safe distance caused 19.43% of accidents, mostly involving forward movement (68.97%). Lane change (10.2%), especially right lane change, was the second leading cause. Abrupt deceleration (7.13%) and left

lane change (5.77%) also contributed, while overtaking was involved in 1.83%. Middle-aged drivers were most involved across all types. Environmental factors showed 75.10% of accidents occurred in sunny weather, 60.63% during the day, mostly from the front (63.57%), often while in traffic lanes (80.73%). Vehicle speeds varied, with 38.53% below 40 km/h and 22.13% at 40-60 km/h. This data highlights key factors in accidents related to drivers and environment.

Variables	Value	Total Number of Accidents	
		Frequency	Percentage (%)
Accident severity	1. Major accident	1147	38.23
	2. Minor accident	1252	41.73
	3. Fatal	601	20.03
Driving license	1. With license	1658	55.27
	2. Without license	1342	44.73
Major cause of accidents	1. Improper lane change	652	21.73
	2. Speeding	500	16.67
	3. Failure to keep safe distance	583	19.43
	4. Driving disability	135	4.5
	5. Failure to pay attention to the front	583	19.43
	6. Brake failure or tire puncture	150	5
	7. Reverse driving	173	5.77
	8. Poor road surface	172	5.73
	9. Others	208	6.93
Action	1. Forward	2096	69.87
	2. Left lane change	173	5.77
	3. Right lane change	306	10.2
	4. Overtaking	55	1.83
	5. Abrupt deceleration	214	7.13
	6. Others	156	5.2
Weather condition	1. Sunny	2253	75.1
	2. Rainy	356	11.87
	3. Fog	391	13.03
Lighting condition	1. Daytime	1819	60.63
	2. Evening	679	22.63
	3. Nighttime with illumination	286	9.53
	4. Nighttime without illumination	216	7.2
Crash position on vehicles	1. Front	1907	63.57
	2. Backside	298	9.93
	3. Car right side	264	8.8
	4. Car left side	163	5.43
	5. Others	368	12.27
Location on road	1. Traffic lane	2422	80.73
	2. Ramp	220	7.33
	3. Shoulder	210	7
	4. Others	148	4.93
Speed of vehicles	1. Below 40 km/h	1156	38.53
	2. 60–40 km/h	664	22.13
	3. 50–70 km/h	492	16.4
	4. 70–80 km/h	382	12.73
	5. More than 80 km/h	306	10.2

Table 2. Descriptive statistics of crash data

3.3 Selecting Target Data

Table 3 presents valuable correlations related to factors influencing the severity of accidents based on an analysis of vehicle crashes in Rajshahi. Driver characteristics include gender, age, whether the driver had a valid license, and the driver's occupation, while information on the vehicle includes vehicles type and region of travel, and the details of the crash, involving major cause of the crash, weather condition at the time of the crash, light condition, positions of the vehicles, locations, and speed among others. The values of the Pearson correlation coefficients are always between -1 and 1, which shows the nature and intensity of these relationships. The findings indicate that accident severity has a positive, medium-scale relationship with the driver's age (0. 59), vehicle type (0. 539), and journey purpose (0. 485), which supports the idea that older drivers, specific vehicle types, and certain journey purposes may be more likely to be involved in severe accidents. On the other hand, there is a relatively higher negative correlation between license status and the severity of the accident (-0.254) to support the high tendency of severe accidents among unlicensed drivers. Furthermore, the coefficient of inter-variable relationship, for instance, a negative relation of vehicle type & license status (-0. 259) and driver's occupation & vehicle type (-0.481) denotes several useful interaction effects which, if addressed properly, ultimately aims at improving road safety. These circumstances highlight the importance of rigorous licensing standards and specific safety measures based on the driver and trip characteristics.

4 RESULTS AND DISCUSSIONS

4.1 Ordered probit regression Model

The ordered probit regression model in "Table 4" shows how the factors described above are influenced by the driver's age, categorized as young, middle, and old. The significant predictors in the analysis are the constant term, accident severity, driver occupation, light condition, and vehicle speed. The constant term, with a coefficient of 0.488 and p-value 0.019, gives the baseline probability of the outcome if all the predic-

	Accident severity	Driver gender	Driver age	Driving License	Vehicle type	Driver occupation	Journey purpose	Major cause	Action	Weather condition	Lighting condition	Crash position	Location on road	Speed of vehicles
Accident severity	1													
Driver gender	-0.11	1												
Driver age	0.59	0.033	1											
Driving License	-0.254	-0.051	0.011	1										
Vehicle type	0.539	-0.151	0.051	-0.259	1									
Driver occupation	0.063	0.121	0.026	0.131	-0.481	1								
Journey purpose	0.485	0.024	0.102	-0.295	0.123	0.185	1							
Major cause	0.004	0.15	-0.007	0.082	-0.023	0.137	0.008	1						
Action	0.003	0.001	0.023	0.231	0.129	0.065	0.023	-0.002	1					
Weather condition	0.016	0.009	0.066	-0.014	0.083	-0.09	-0.011	0.005	0.023	1				
Lighting condition	0.081	0.025	0.064	-0.164	0.121	-0.045	0.013	0.107	0.067	0.089	1			
Crash position	-0.031	-0.076	0.015	0.12	-0.025	0.073	0.067	0.029	0.102	0.102	0.024	1		
Location on road	0.02	0.022	0.008	0.016	0.017	0.014	0.005	0.198	-0.003	0.119	0.12	0.091	1	
Speed of vehicles	0.002	0.042	0.125	0.062	-0.047	0.118	0.024	0.019	0.125	-0.01	-0.026	0.001	0.017	1

Table 3 Relationship among the variables (Correlation)

Variables	β	St. Err.	p-value	[95% Conf Interval]		Sig
Constant (Driver age)	0.488	0.220	.019	0.097	0.803	**
Accident severity	0.092	0.041	.024	0.012	0.172	**
Driver gender	0.236	0.147	.111	-0.053	0.525	
Driving license	0.063	0.068	.352	-0.069	0.195	
Vehicle type	0.028	0.018	.116	-0.007	0.063	
Driver occupation	0.239	0.033	.001	0.174	0.304	***
Journey purpose	0.059	0.032	.066	-0.004	0.123	*
Major cause of accidents	-0.021	0.013	.125	-0.046	0.006	
Action	-0.069	0.371	.355	0.063	0.312	
Weather condition	0.031	0.044	.483	-0.056	0.118	
Light condition	-0.094	0.035	.007	-0.163	-0.026	***
Crash position on vehicles	-0.020	0.025	.417	-0.068	0.028	
Location on road	0.046	0.037	.213	-0.026	0.117	
Speed of vehicles	0.553	0.022	.001	0.509	0.596	***

**** p< .01, ** p< .05, * p< .1*

Table 4 Ordered probit regression Model

tors are zero. The accident severity is significant at 5% with a coefficient of 0.092 and p-value 0.024, indicating that the higher the severity of accidents, the greater the chances that drivers will belong to the Middle age categories. The driver's occupation is highly significant, $p < 0.01$, with a coefficient of 0.239, thus showing a strong association with older driver categories. Lighting condition is highly significant at the 1% level, with a coefficient of -0.094 and a p-value of 0.007, denoting that bad lighting conditions decrease the probability of older age categories. Vehicle speed is one of the most important predictors according to the size of the coefficient: it is 0.553, with $p < 0.01$, showing that higher vehicle speeds increase the probability of older age categories significantly. Other variables that were not significant predictors in the model were driver gender, driving license, type of vehicle, the purpose of the journey, the major cause of accidents, weather conditions, the crash position of vehicles, and location on the road.

4.2 Poisson regression Model

The Poisson regression model in "Table 5" estimates the effect of factors on the accident count. There are several important conclusions. The constant term is significant at a 5% level with a coefficient of 0.448 and a p-value of 0.013, thereby setting up an average count of accidents as a baseline. The variable driving license status is significant at a 5% level with a coefficient of 0.019 and p-value 0.042, indicating that having a driving license is associated with higher count factors for accidents. The driver occupation variable is significant at the 5% level, having a coefficient of 0.032 with $p = 0.018$, hence indicating a positive relationship between occupation and accident count. Major cause of accident variable is significant at 5% level with a negative coefficient of -0.002, having p value 0.033 indicating major causes reduce accident count. Vehicle speed is very highly significant, with a coefficient of 0.077 and $p < .01$; this implies that with high vehicle speeds, there will be more accidents. Other variables of accident severity, driver gender, vehicle type, journey purpose, weather conditions, light conditions, crash position on vehicles, and location on the road all made nonsignificant predictions in this model.

4.3 Gamma regression Model

The Gamma regression model shown in "Table 6" estimated the effects of the various predictors on the accident severity score. The constant term is significant at $p< 0.01$ with a coef-

Variables	β	St. Err.	p-value	[95% Conf Interval]		Sig
Constant (Driver age)	0.448	0.180	.013	0.095	0.801	**
Accident severity	0.009	0.016	.546	-0.021	0.040	
Driver gender	0.041	0.064	.516	-0.083	0.166	
Driving license	0.019	0.025	.042	-0.030	0.069	**
Vehicle type	0.003	0.007	.674	-0.010	0.016	
Driver occupation	0.032	0.014	.018	0.006	0.059	**
Journey purpose	0.006	0.012	.621	-0.018	0.030	
Major cause of accidents	-0.002	0.005	.033	-0.012	0.007	**
Action	0.006	0.017	.743	-0.320	0.401	
Weather condition	0.002	0.016	.899	-0.030	0.034	
Light condition	-0.009	0.012	.446	-0.033	0.015	
Crash position on vehicles	-0.002	0.009	.786	-0.020	0.015	
Location on road	0.004	0.014	.768	-0.023	0.032	
Speed of vehicles	0.077	0.008	.001	0.061	0.094	***

*** p< .01, ** p< .05, * p< .1

Table 5 Poisson regression Model

Variables	β	St. Err.	p-value	[95% Conf Interval]		Sig
Constant (Driver Age)	1.290	0.142	.001	1.010	1.570	***
Accident severity	0.026	0.013	.041	0.001	0.050	**
Driver gender	0.106	0.050	.033	0.009	0.204	**
Driving license	0.050	0.020	.014	0.010	0.090	**
Vehicle type	0.007	0.005	.168	-0.003	0.018	
Driver occupation	0.085	0.011	.001	0.064	0.106	***
Journey purpose	0.017	0.010	.088	-0.002	0.036	*
Major cause of accidents	-0.006	0.004	.116	-0.014	0.002	
Action	-0.239	0.172	.749	0.065	0.196	
Weather condition	0.006	0.013	.650	-0.020	0.032	
Light condition	-0.026	0.010	.010	-0.045	-0.006	***
Crash position on vehicles	-0.007	0.007	.362	-0.021	0.008	
Location on road	0.011	0.011	.309	-0.011	0.034	
Speed of vehicles	0.204	0.007	.001	0.191	0.217	***

*** p< .01, ** p< .05, * p< .1

Table 6 Gamma regression Model

ficient of 1.29. It is the baseline severity score in the absence of all factors. Accident severity is significant at the 5% level with a coefficient of 0.026 and a p-value of 0.041. It means that higher accident severity scores increase the outcome. Gender is significant at the 5 percent level with a coefficient of 0.106 and a p-value of 0.033. Therefore, gender affects accident severity. The status of the driving license is significant at the 5% level, with a coefficient of 0.05 and p-value equals 0.014, indicating that having a license increases the severity score. The driver's occupation is highly significant with a p-value less than 0.01 and a coefficient of 0.085; it thus shows a large positive effect on severity. Light condition: Significant at the 1 percent level with a coefficient 0.026 and p-value equals 0.01, the better the lighting conditions, the less the severity. The most significant predictor is vehicle speed, whose coefficient is 0.204 with $p < 0.01$, which shows that higher speeds raise the severity of accidents. Variables relating to vehicle type, journey purpose, major cause of accidents, weather conditions, crash position on vehicles, and location on the road were not significant predictors in this model.

Overall, this study found the statistical significance of various factors in relation to the age of drivers across three different regression models. These factors included Accident severity, Speed of vehicles, Driver occupation, Driving license, Lighting condition, Journey purpose, Major cause of accidents, and Driver gender. The findings presented in this paper show that all of these variables were statistically significant concerning the driver's age in all three models.

4.4 Summary of model goodness of fit tests

"Table 7" shows the comparison of three different models across different parameters. The lower values of scaled deviance and Pearson's chi-square per degree of freedom imply that this model fits the data well, showing that the observed data align closely with the model's predictions. However, the higher the AIC and BIC values of a model, the higher the chances of overfitting, suggesting it may not be the most concise since it includes more parameters relative to explaining data variability.

Comparing the statistical models based on AIC and BIC values, the ordered probit regression model was found to have the best fit, considering both goodness of fit and model complexity. While the Poisson regression model returned the lowest scaled deviance and Pearson chi-square values, it was penalized by higher AIC and BIC values, which pointed to overfitting or higher complexity. It gives a reasonable fit with moderate complexity, and the additional parameters do not pay out in terms of goodness of fit compared to the ordered probit model. Thus, an ordered probit regression model would be most suitable to explain the data, offering the best compromise between fit and simplicity. The Poisson regression model is less favoured because it is of higher complexity for its good fit, as reflected in both AIC and BIC values. A gamma regression model fits very well, but it does not show the same balance of fit and simplicity as ordered probit Regression.

"Table 8" presents a summary of the statistically significant results in the three models that were used in the analysis: Ordered Probit, Poisson, and Gamma. In the Ordered Probit model, the values of Accident severity, Driver occupation, Light condition, as well as the Speed of vehicles have a significant impact on crash severity differently ($p<.01$, $p<.05$, $p<.1$). In the following paper, an extensive focus has been made on the Poisson model, where the aspects of Driving license, Driver occupation, Major cause of accidents, and Speed of vehicles have been addressed for analysing crash frequency which is useful for count data. The gamma model that deals with continuous and positively skewed data underlines some key factors that define crash economic and temporal consequences such as Accident severity, Driver gender, Driving license, and Speed, among others. Altogether, these models provide a balanced view of factors related to vehicle crashes. All these models are appropriate for diverse sorts of data and distinct aspects of the crash analysis.

4.5 Odds Ratio of Variables

Besides their statistical significance, the outputs predicted by the three regression models are presented in "Table 9", which involved coefficients and odds ratios for different variables. These outputs represent the relative correlation of each value of a given variable with specific levels of accident severity. With odds ratios of 1.591, 1.426, and 1.381 across three models, improper lane change is the most significant cause and is strongly correlated with serious accidents. Speeding has odds ratios of 1.192, 1.142, and 1.134, indicating a positive but weaker association with severity. Failure to keep safe distance shows a comparatively less correlation with odds ratios is 1.079, 1.059 and 1.054. The higher

Regression models	Degree of freedom (DF)	Scaled deviance/DF	Pearson Chi-Square value/DF	Log likelihood	AIC	BIC
Ordered probit regression Model	13	26.8	16.41	-1353.392	2734.78	2818.87
Poisson regression model	13	25.97	22.23	-4486.891	8999.78	9077.86
Gamma regression model	13	54.6	54.6	-2094.72	4215.45	4293.53

Table 7 Summary of model goodness of fit tests

	Ordered probit regression Model	Poisson regression Model	Gamma regression Model
Statistically significant variables	Accident severity**	Driving license**	Accident severity**
	Driver occupation***	Driver occupation**	Driver gender**
	Journey purpose*	Major cause of accidents**	Driving license**
	Lighting condition***	Speed of vehicles***	Driver occupation***
	Speed of vehicles***		Journey purpose*
			Lighting condition***
			Speed of vehicles***

*** p< .01, ** p< .05, * p< .1

Table 8: Comparison table for different significant factors of those models

Variables	Value	Ordered Probit Regression Analysis			Poisson Regression Analysis			Gamma Regression Analysis		
		Coefficient	P-value	Exp (Coefficient)	Coefficient	P-value	Exp (Coefficient)	Coefficient	P-value	Exp (Coefficient)
Major cause of accidents	Improper lane change	0.464	0.002	1.591	0.355	0.018	1.426	0.324	0.025	1.381
	Speeding	0.176	0.255	1.192	0.132	0.367	1.142	0.122	0.398	1.134
	Failure to keep safe distance	0.077	0.622	1.079	0.058	0.563	1.059	0.052	0.595	1.054
	Driving disability	0.376	0.015	1.456	0.282	0.024	1.327	0.251	0.032	1.284
	Break failure or tire puncture	0.244	0.115	1.276	0.183	0.156	1.199	0.162	0.176	1.177
	Reverse driving	0.000	1.000	1.000	0.000	1.000	1.000	0.000	1.000	1.000
	Others	0.000	1.000	1.000	0.000	1.000	1.000	0.000	1.000	1.000
Action	Forward	-0.464	0.002	0.629	-0.355	0.018	0.699	-0.324	0.025	0.724
	Left lane change	0.464	0.002	1.591	0.355	0.018	1.426	0.324	0.025	1.381
	Right lane change	0.000	1.000	1.000	0.000	1.000	1.000	0.000	1.000	1.000
	Overtaking	0.077	0.622	1.079	0.058	0.563	1.059	0.052	0.595	1.054
	Abrupt deceleration	0.376	0.015	1.456	0.282	0.024	1.327	0.25	0.032	1.284
	Others	0.244	0.115	1.276	0.183	0.156	1.199	0.162	0.176	1.177

Table 9. Estimation result Odds Ratio between "Major cause of accidents" and "Action"

odds ratios of 1.456, 1.327, and 1.284 for driving disability show a strong correlation. Actions such as forward driving are associated with minor accidents, with ratios below 1, whereas left lane change and abrupt deceleration are associated with higher ratios, indicating a higher likelihood of severe accidents. Overtaking shows a weak relation with accidents. Finally understand, improper lane change, driving disability, and left lane change have the highest correlations with severe accidents. In these circumstances like driving forward and failure to keep a safe distance are linked to minor accidents. Understanding how causes and actions affect accident severity is made easier by taking into consideration the findings from three models, showing the importance of solving these issues.

5 CONCLUSION

This study explores the relationship between driver's different age groups like young, middle and older age characteristics and they related to various crash-related factors. Also analysing these age groups are influenced crash patterns outcomes especially which age groups are highly involved in road crash in Bangladesh. The Ordered Probit Model, Poisson Regression Model, and Gamma Regression Model were applied to analyse the data collected from the DBQ. The Ordered Probit Model of the three had the best balance between complexity and accuracy in the process of figuring the majority age group and unique predictors of those crashes.

The analysis revealed several factors significantly influencing crash involvement across driver age groups. Those are vehicle speed, driver occupation, lighting conditions and the accident severity. The findings from this study differ from those of similar studies in developed countries. Speed emerged as the most influential factor indicating that higher-speed crashes are more commonly associated with older driver age groups (middle-aged). Aggressive driving behaviours are most prevalent among middle-aged male drivers in Bangladesh. Individuals in the middle-age category tend to be involved in more accidents than other groups, whereas in developed countries, young drivers are more engaged in road crashes. 'Improper lane change' increases the odds of crash involvement by approximately 38-59% depending on the model. Driving disability also demonstrates a substantial increase in crash likelihood. 'Left lane change' has emerged as one of the most critical driving actions that increases the likelihood of a crash involvement. Abrupt deceleration also showed significant influence suggesting crash risk during sudden braking situations. Strict regulations should be enforced on roads to address aggressive driving behaviour, particularly among middle-aged male drivers. Drivers with disabilities striving to provide for their families should receive essential government grants and safety support materials. Driving knowledge, particularly about lane changes should be a top priority.

However, some key limitations can be considered in this study: 1) The analysis didn't include crash data from any authority or department that stores such data. 2) In this research, survey areas were in Rajshahi City. The drivers from the selected locations were interviewed. Necessary data was collected using DBQ only from those selected locations. If this research could include crash data from relevant departments and could perform surveys in other cities in Bangladesh, then the findings would have become more appropriate. More comprehensive data leads to greater accuracy, so future research should focus on expanding data collection to other parts of Bangladesh.

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