EXPLORING DRIVER PEDESTRIAN INTERACTION USING ALTERNATIVE SEVERITY MODELLING APPROACH: A CASE STUDY FOR DHAKA CITY

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ABSTRACT

Bangladesh holds the 106th global position concerning road-linked fatalities. Annually, traffic incidents lead to approximately 12,000 fatalities and around 35,000 injuries, signifying a stark reality of roughly 32 daily fatalities in road mishaps. These accidents' instigators are significantly influenced by the vehicles' maneuvering capabilities. Conversely, in Bangladesh, pedestrians remain the most disregarded faction with respect to research and safety precautions, despite their involvement in nearly half of all lethal collisions.The study's main objective revolves around assessing the seriousness of accidents within Dhaka Metropolitan City. It does so by scrutinizing driver maneuvers and pedestrian attributes as the dependent variables. To gather data about traffic accidents in Dhaka from 2017 to 2020, the researchers collaborated with the Accident Research Institute (ARI) at BUET. The study hinges on two well-established models: the Multinomial Logit (MNL) and the Ordered Logit (OL).The findings spotlight the city of Dhaka, emphasizing that turns, both left and right, wield more influence than other driving actions. Preeminent risks are linked to male pedestrians and those aged over 50 years. Notably, pedestrians walking close to a road's center are at a higher peril of being engaged in fatal accidents compared to those situated in other areas and circumstances.

Keywords: *accident, fatalities, safety, pedestrian, vehicles.*

1. INTRODUCTION

Car crashes impose substantial financial burdens on individuals, their families, and entire nations, leading to an approximate 3% of GDP expense in many countries. More than 50% of road traffic fatalities are attributed to vulnerable road users, such as pedestrians, cyclists, and motorbike riders. Low and middle-income nations, despite having a significant share of the world's vehicles, bear the primary burden of road fatalities, with a particular impact on young people. Bangladesh is ranked 106th globally in terms of deaths caused by road accidents, with buses and trucks being significant contributors. Accurate accident data in Bangladesh is often lacking, necessitating comprehensive research to address the root causes and enhance road safety. The primary aim of this study is to analyze the interaction between driver maneuvers and pedestrian actions in Dhaka Metropolitan City accidents from 2017 to 2020 using data from the Accident Research Institute (ARI), BUET. It specifically assesses the applicability of probabilistic models in the context of Bangladesh's economic development. The study's specific objectives include evaluating accident severity related to driver maneuvers, understanding pedestrian accident severity in Dhaka, and assessing accident severity variables using MNL (Multinomial Logit) and OL (Ordered Logit) models. Dhaka, the capital of Bangladesh, experiences the worst road collision rates compared to other cities, with over 10,000 accidents between 1998 and 2014, resulting in 4,514 pedestrian fatalities, constituting 72% of all traffic deaths. Studying pedestrian vulnerability and factors contributing to maneuvering-pedestrian-vehicle accidents is crucial.

There have been limited studies on the connection between driver maneuvers and pedestrian actions impacting accident severity. Rakib and Hoque (2003) investigated aggressive driving behavior, finding competitive overtaking and unanticipated pedestrian behavior as key factors. Ahsan et al. (2011) examined vehicle accidents, identifying pedestrian involvement but not addressing the relationship with maneuvers. Tanvir (2018) studied accident severity, highlighting fatal accidents during straight car movement, particularly affecting pedestrians. Mithun et al. (2021) focused on pedestrian behavior, revealing cognitive patterns that can influence pedestrian decision-making and crash risk. Sarkar et al. (2011) discovered higher pedestrian mortality risk near roads and in accidents involving buses or minibuses, investigating factors contributing to fatal accidents.

Chia et al. (2014) found that left-turning transit buses pose a higher accident risk with pedestrians on the right side. Rami et al. (2009) used the GES database from 2002 to 2004 to investigate evasive behaviors before crashes. They discovered that impaired visibility had the biggest impact on evasive maneuvers in head-on and angle collisions, followed by distracted driving. Younger drivers (<35) were more likely to make evasive moves in rear-end crashes. Driver inattention is a common factor in accidents. Pawar and Patil (2017) studied how phone use affects drivers at unsignalized junctions. Phone use led to slower reaction times but did not affect driving speed. Sigal and Carlo (2015) looked at crash avoidance maneuvers and found the critical event, gender, drowsiness, and road conditions influenced drivers' choices. Febres et al. (2021) explored pedestrian culpability in traffic accidents, finding that pedestrian behavior significantly affects injury severity. Bashar and Eman (2013) investigated pedestrian accidents in Irbid, emphasizing that most injuries resulted from not giving pedestrians the right of way. Abbas et al. (2020) studied vehicle-pedestrian interactions in marked and unmarked crosswalks, revealing similar behavioral patterns and conflict intensity effects on evasive maneuvers between cars and pedestrians.

Fan and Lord (2013) investigated sample size requirements for crash severity models: multinomial logit, sorted probit, and mixed logit, using data ranging from 100 to 10,000 observations. They found that small sample sizes significantly impact crash severity model development, with the mixed logit model needing the largest sample and the ordered probit model needing the smallest.

Zhen and Wei (2018) used a multinomial logit (MNL) model on North Carolina pedestrian-vehicle accident data, identifying factors affecting injury severity. Shankar and Mannering (1996) employed MNL for Washington motorcycle crash data, highlighting the impact of helmet use on fatality. Vajari et al. (2020) examined motorcycle accidents in Victoria using an MNL model, identifying conditions increasing the likelihood of fatal injuries. Himanen and Risto (1988) investigated pedestrian and motorist behavior at crossings, using an MNL model to analyze factors like vehicle speed and city size. Tay et al. (2011) applied the MNL model in South Korea, finding factors associated with fatal and serious pedestrian-vehicle crashes, including driver characteristics and environmental conditions.

Tageldin & Sayed (2017) explored pedestrian confrontations in various global cities, using temporal proximity and evasive action indicators to assess conflict severity. In less organized traffic areas like Shanghai and New Delhi, the evasive action-based indicator proved more effective, while in structured locations like Vancouver, the time proximity measure performed better. O'Donnell and Conner (1996) examined road user characteristics and their influence on injury severity in motor vehicle accidents using ordered models, finding factors like age, vehicle speed, sitting position, blood alcohol level, gender, accident type, and vehicle type played significant roles. Choi et al. (2009) investigated nationwide pedestrian collisions in 2006, utilizing an Ordered Logit Model to study contributing variables such as gender, age, alcohol consumption, vehicle type, road geometry, weather, and time of day, revealing their impact on crash severity.

Shamsunnahar et al. (2013) focused on modeling pedestrian injury severity in New York City, using ordered response models (OL, GOL, and LSOL). They found that OL/OP models couldn't capture unique risk factors for specific injury categories, while GOL allowed for variable effects on threshold values, and LSOL segmented the pedestrian population for differential influences. Rabbi et al. (2022) assessed three statistical models (MNL, OL, PPO) to analyze pedestrian collision severity in Dhaka, identifying factors like road type, vehicle type, seat belt use, age groups, and pedestrian behavior. Li and Wei (2019) examined pedestrian safety by age group using a partial proportional odds (PPO) model, showing better results with distinct models for each group. Lekshmi and Monica (2014) introduced the PPO model to bridge the gap between ordered and unordered injury severity modeling, accommodating varying effects on different severity levels. Kibrom (2013) studied pedestrian injuries in Denmark and found that random parameters models outperformed fixed-parameters models in capturing variable effects. Iranitalab and Khattak (2017) compared the accuracy of four prediction methods for crash severity and noted that NNC performed the best, with clustering methods enhancing MNL, NNC, and RF. Zong et al. (2013) explored Bayesian networks and Regression models to predict traffic accident severity, with Bayesian networks outperforming the Regression models. Garrido et al. (2014) investigated injury severity in motor-vehicle passengers in Portugal, highlighting factors such as seating position, gender differences, metropolitan regions, and vehicle size that influenced injury outcomes.

The primary objective of this research is to evaluate the severity of accidents in the Dhaka Metropolitan Area, with a special focus on the dependent variables of driver behaviour and pedestrian behaviour. The Bangladesh University of Engineering and Technology's Accident Research Institute (ARI) provided the study with road accident data from 2017 to 2020 (BUET). The research specifically looks at the suitability of discrete-outcome probabilistic models in relation to Bangladesh's economic growth. The study aims to obtain a thorough understanding of accident severity resulting from driver manoeuvring, investigate the severity of pedestrian accidents in Dhaka, and apply Multinomial Logit (MNL) and Ordered Logit (OL) models to obtain insights into accident severity variables.

2. METHODOLOGY

This study encompasses three fundamental tasks conducted through analytical methods: firstly, comprehending the existing state of traffic safety in Bangladesh; secondly, employing probabilistic approaches to scrutinize crash data for unanticipated future outcomes, utilizing accident data supplied by the Accident Research Institute (ARI) and initiating basic cross-tabulation in Microsoft Excel; and finally, selecting an appropriate methodology via comparative research specific to the country. The paramount phase involves the analysis of the data in the R programming environment using discrete response models, namely the multinomial logit (MNL) model and ordered logit (OL) model. The culmination of this investigation involves the careful selection of a fitting model based on adequacy

and the comparison of variables that most effectively address the data crisis within the context of Bangladesh. The subsequent sections sequentially outline the stages associated with these tasks.
The methodological procedures that were performed in order to engineer the objective of this thesis

Cross-tabulation in Microsoft Excel using the accident data to comprehend the severity of injuries and examine the multicollinearity of factors.

Using R to analyze ordinal and nominal models to predict injury severity results.

Investigating and cross-validating the prediction models to determine which ones are most appropriate.

are shown in the following image:

Figure 1: Flow Diagram of the Paper

2.1 Data collection and Description

For the purposes of this study, accident data from Dhaka Metropolitan City spanning the years 2017 to 2020 was collected from the Accident Research Institute (ARI). The dataset, derived from accident police reports, encompasses comprehensive details of incidents occurring during the specified period. The collected information includes accident location (Thana, District), details of vehicles and individuals involved (number of vehicles, driver casualties, passenger casualties, pedestrian casualties, accident severity), accident date and time (day of the week, date in the month), road geometry and weather conditions (junction type, traffic control, collision type, movement, divider, weather, light, road geometry, surface condition, surface type, surface quality, road class, road feature), mapping details (location type, XY map code, X coordinate, Y coordinate, route number, kilometre post x100 meters, node map code, node 1, node 2), vehicle particulars (district of registration, vehicle registration, fitness certificate, district of license issue, license number), vehicle condition (vehicle type, vehicle manoeuvre, vehicle loading, vehicle defects, vehicle damage), and details about drivers, passengers, and pedestrians (driver sex, driver age, driver injury, alcohol involvement, seat belt usage, passenger vehicle code, passenger sex, passenger age, passenger injury, position in vehicle, passenger action, pedestrian vehicle code, pedestrian sex, pedestrian age, pedestrian injury, pedestrian location, pedestrian action). Additionally, the dataset includes information on contributory factors, accident description, and location description.

2.2 Multinomial Logit Model

The presented model revolves around certain key assumptions and mathematical formulations for analysing injury severity in the context of transportation. The assumptions include the specification that data is level-specific, with distinct unit values for each character, and the disregard of the sequential sequence of response variable levels. The independence of irrelevant alternatives (IIA) is essential for the model's functionality. The mathematical interpretation introduces the probability of an observation sustaining a particular injury severity level, expressed through a function of covariates (Uni) and a linear-in-parameter form. The model assumes an extreme value type 1 distribution for disturbance terms, specifically a Gumbel distribution, which aligns with the desired conditions for the disturbance term. The probability density function (pdf) and cumulative distribution function (cdf) for this distribution are presented. The generalized extreme value assumptions lead to the formulation of a standard multinomial logit model, where a vector of parameters (β's) is estimated using maximum likelihood (ML) techniques. The log-likelihood function is detailed for a sample of observations. Model identification involves setting restrictions on parameters for recognition. The model is made recognizable by substituting parameters, and the resulting probability equation for observed events is provided. The summary encapsulates the model's underlying assumptions, mathematical formulations, and identification procedures for studying injury severity in transportation contexts.

2.3 Ordered Logit Model

The Ordered Logit (OL) Model is introduced, incorporating crucial assumptions and mathematical interpretations for analysing injury severity in a latent variable framework. The model assumes the Parallel Odds Assumption, asserting that the influence of an independent variable is consistent across all levels of the response variable. The disturbance term is assumed to be logistically distributed among observations, with zero correlation between disturbance terms for distinct observations and homoscedastic characteristics. The mathematical interpretation presents the general specification of the Proportional Odds (PO) model, expressed as a latent variable assessing the probability of harm in a collision. The model's logistically distributed error component is detailed with probability density and cumulative density functions. The latent variable's unavailability leads to the use of observable and coded discrete injury severity variables, creating relationships between these and the latent variable. The log-likelihood function for a sample of observations is formulated, involving the estimation of parameters using the maximum likelihood technique. Model identification challenges arise due to the latent nature of the variable, and assumptions are made to render the model identifiable. The summary encapsulates the model's assumptions, mathematical formulation, and challenges in model identification in the context of analysing injury severity.

2.4 Fit Adequacy

The "goodness of fit" in modelling, assessing how well a paradigm aligns with observed data, is crucial. Tests like AIC, BIC, and McFadden's Pseudo R-Squared are commonly used for fit adequacy assessment. Additionally, MAPE analyses error percentages in severity analysis and finds application in various contexts.

2.4.1 Akaike Information Criterion (AIC)

The AIC serves as a relative measure of statistical model quality, aiding in model selection for a given dataset. Represented by,

$$AIC = -2\ ln\ (L) + 2k \tag{1}$$

where L is the maximum likelihood function value, and k is the number of model parameters, AIC favours models with high log-likelihood and low AIC values, indicating better fitness. The penalty term 2k accounts for overfitting, considering an increase in model parameters. AIC doesn't warn about poor-fitting models but evaluates their relativity, estimating the lost information in the modelling process. Models are chosen based on their ability to minimize information loss.

2.4.2 Bayesian Information Criterion (BIC)

Model selection using the Bayesian Information Criterion (BIC), closely related to the Akaike Information Criterion (AIC), involves evaluating,

$$BIC = -2 \ln (L) + \ln (n) k, \quad (2)$$

where L is the model's maximum likelihood value, k is the number of estimated parameters, and n is the sample size. BIC assumes a significantly larger sample size than the model parameters. The model with the lowest BIC is preferred, similar to AIC. BIC addresses overfitting, but its penalty term is larger than AIC's 2k-unit penalty, and it's suitable only when response values are consistent across compared models.

2.4.3 McFadden's Pseudo

McFadden's ρ^2 statistic is commonly used in model fitting, akin to its role in regression models. Expressed as,

$$\rho^2=1- (LL(\beta))/(LL(0)), \quad (2)$$

where LL(β) is the model's log likelihood at convergence and LL(0) is the log likelihood when all parameters are set to 0, it serves as a likelihood ratio index. With values ranging from 0 to 1, a ρ^2 close to 1 signifies high-confidence parameter estimation.

3. RESULTS

3.1 Results of Model Estimation

Using R, four accident severity models were developed, and the most suitable model for the available data was selected. Feature selection involved identifying elements impacting severity levels, with significance determined by p-values below 0.05 (95 percent confidence). A key conviction was established: if any category of an independent variable proved statistically significant, the entire variable was considered significant in determining injury severity in major vehicular collisions. Consequently, even seemingly unimportant elements were included in the final model due to their potential influence on triggering factors.

3.1.1 Interpretation of MNL Result

Because the outcome variable of accident severity is categorical, we used the MNL model for the crash data. Following is a summary of the estimated findings of the MNL model shown in Table 3.1

Table 3.1: : Estimation Results of Multinomial Logit Model

Variables	Grievous			Fatal		
	Coefficient	S.E.	P Value	Coefficient	S.E.	P Value
(Intercept)	-0.154	0.524	0.769	0.28	0.513	0.586
Vehicle Maneuver (base: others)						
Left Turn/Right Turn	13.678	0.198	0	14.611	0.198	0
Overtaking	-1.473	0.434	0.001	-1.336	0.425	0.002
Going Ahead	-1.261	0.329	0	-1.419	0.329	0
Pedestrian Sex (base: female)						
Male	0.372	0.2	0.063	0.287	0.206	0.163
Pedestrian Age (base: <19)						
19-30	-1.669	0.367	0	-0.346	0.414	0.403
31-40	-1.118	0.371	0.003	0.03	0.417	0.943
41-50	2.639	0.791	0.001	4.092	0.81	0
>50	17.863	0.198	0	18.82	0.198	0
Pedestrian Location (base: On pedestrian Crossing/Footpath)						

Road Centre	0.773	0.554	0.163	-1.201	0.481	0.012
Pedestrian Action (ref: no action)						
Crossing the road	1.166	0.576	0.043	1.508	0.551	0.006
Walking along with the road/ Playing on the road	0.982	0.598	0.1	1.629	0.545	0.003
Log-Likelihood at convergence	-963.5203					
AIC	1975.0407					
BIC	2094.293					

The table is categorized into two sections for serious damage and fatal injury, maintaining a zero coefficient for simple injury as the baseline. Calculated coefficients reveal the relative importance of characteristics in grievous and fatal injury severity compared to simple injury. Positive coefficients signify increased severe damage risk, while negative coefficients indicate a lower likelihood of harm than simple injury. Despite categorical variables having individual base categories, simplicity is prioritized in analysis, underscoring simple injury as the fundamental collision severity category.

Analysis of coefficients in Table 5.2 suggests that left and right turns pose a higher risk for death and severe harm compared to other vehicle maneuvers, supported by a p-value less than 0.05, indicating statistical significance. Conversely, moving ahead and overtaking carry a lower risk of death and serious injury than alternative maneuvers. Examining gender disparities, male pedestrians exhibit a higher likelihood of fatal or major injury compared to females, although not statistically significant. This observation contradicts previous research, hinting at potential gender-based risk-taking behaviour influencing outcomes in fatal and major injury crashes.

Pedestrian age is a crucial factor in accident outcomes. Individuals aged 19-40 are less likely to experience fatal accidents than those under 18 but are more prone to serious injuries. However, those over 40, especially above 50, are at a higher risk of both fatal and serious injuries. While statistically significant for grievous injuries, the findings emphasize the severe consequences of collisions involving older pedestrians and larger vehicles. Walkers near a road centre face a higher risk of fatal injury than those near pedestrian crossings, but they are less likely to suffer severe injury compared to those on the road's edge. Pedestrian crossings and traffic lanes emerge as conflict zones, contributing to a greater risk of severe harm. Crossing the road or playing on it increases the likelihood of fatal and grievous injuries compared to inaction, with significant statistical significance in fatal injury cases.

3.1.2 Interpretation of OL Result

When applying the OL model to crash data, consideration of the ordinal nature of accident severity is crucial. Positive parameter values increase the probability of higher severity, while negative values decrease it.

Table 3.2: Estimation Results of Ordered Logit Model

Variables	Coefficient	S.E.	t Value	P Value
Vehicle Maneuver (base: others)				
Left Turn/Right Turn	0.976	0.384	2.541	0.988
Overtaking	-0.780	0.279	-2.795	0.988
Going Ahead	-0.837	0.192	-4.342	0
Pedestrian Sex (base: female)				
Male	0.164	0.140	1.167	0.868
Pedestrian Age (base: <19)				
19-30	-0.308	0.249	1.239	0.119
31-40	0.091	0.253	0.359	0.637
41-50	1.547	0.272	5.681	1.000
>50	1.300	0.282	4.606	1.000
Pedestrian Location				
Road Centre	-0.965	0.302	-3.185	0.004

Pedestrian Action				
Crossing the road	0.977	0.350	2.787	0.992
Walking along with the road/ Playing on the road	1.471	0.376	3.908	0.999
S|F	-0.956	0.348	-2.742	0.008
F|G	0.698	0.348	2.004	0.967
Log-Likelihood at convergence	-1044.758			
AIC	2115.517			
BIC	2180.1128			

In the analysis of the OL model coefficients, "left turn/right turn" in vehicle movement increases the likelihood of severe accidents with fatal injuries. Male pedestrians face a higher risk of death, especially when struck by large vehicles between ages 41 and 50. Pedestrians near the road centre are more prone to simple injuries. Engaging in activities like strolling or playing on the road increases the likelihood of fatal injuries compared to crossing the road. The comparison of coefficients prioritizes factors, with overtaking having the least influence on causing fatal harm. The findings provide valuable insights into the factors influencing accident severity.

3.2 Comparative Study

Comparing the values from Table 3.1 and 3.2, it was determined that the MNL model has been the most efficacious when compared to other models in aspects of Log likelihood, AIC, and BIC.

Table 3.3: Results in Terms of Significant Predictors

Variables	**Models**	
	MNL	**OL**
Vehicle Maneuvers	√	√
Pedestrian Sex	×	×
Pedestrian Location	√	√
Pedestrian Action	√	×
Pedestrian Age	√	×

The comparison of models (Table 3.3) focused on the significance of forecasts in large vehicle accidents. Statistically significant categories of explanatory factors in the MNL model imply overall significance in influencing injury severity. With more significant factors, the MNL model is better suited for studying accident severity in the Dhaka Metropolitan region.

4. CONCLUSIONS

The study's key findings highlight the superior performance of the MNL model in comparison to others, making it a more suitable choice for analyzing accident severity in Dhaka. It emphasizes that certain vehicle maneuvers, particularly left and right turns, pose higher risks than others. Additionally, it notes the gender disparity among pedestrians, with males facing a higher risk of severe outcomes, contrary to previous studies that suggest greater survival chances for females in fatal accidents. The age factor reveals a lower frequency of fatal accidents but higher major injuries in the 19-40 age group, while individuals over 40, especially those over 50, are at a higher risk of fatal injuries. Pedestrians near road centers face higher fatality risks but lower severe injury risks.

The policy implications derived from the findings include addressing pedestrian safety through improved infrastructure, educating and accommodating older pedestrians, emphasizing proper signaling and intersection design for drivers, and enhancing visibility for pedestrians, particularly at night, to reduce accidents.

However, the study acknowledges certain limitations. It recognizes the need to explore more advanced modeling techniques like neural networks and the inclusion of additional features for a comprehensive understanding. The absence of records for crashes with less serious injuries is noted as a limitation, along with the acknowledgment that the assumptions made by the current approaches constrain the effectiveness of crash severity modeling. The study concludes by suggesting a direction for future research, emphasizing the exploration of more sophisticated modeling strategies beyond fundamental models for improved accuracy in crash severity prediction.

ACKNOWLEDGEMENTS

In addition to the contributing authors, acknowledgments are extended to the faculty members, officers, and administrative staff of the ARI for their collaborative efforts. A special mention is dedicated to B.M. Tazbiul Hassan Anik, an alumnus of the Civil Engineering department at BUET, whose continuous support and guidance significantly influenced the progress of this project. Lastly, heartfelt gratitude is extended to the parents of the authors for their generous support, patience, and assistance in facilitating the completion of this work.

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