CRASH SEVERITY MODELLING INVOLVING PUBLIC BUS CRASHES IN DHAKA CITY

MD FERDOUS AHMED

M.Sc. ENGINEERING THESIS

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MD FERDOUS AHMED (SN: 0419110013)

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By

MD FERDOUS AHMED (0419110013)

Approved as to style and content by the Examiners in January 2023:

Brig Gen Shah Md Muniruzzaman (Retd) Professor Department of Civil Engineering MIST, Dhaka	Chairman (Supervisor)
Dr. Md Asif Raihan Assistant Professor Accident Research Institute BUET, Dhaka	Member (Co Supervisor)
Dr. Md. Hadiuzzaman Professor Department of Civil Engineering BUET, Dhaka	Member (External)
Lt Col Mohammed Russedul Islam, PhD Instructor Class A Department of Civil Engineering MIST, Dhaka	Member (Internal)
Brig Gen Md Wahidul Islam, SUP, ndc, psc Head of the Department Department of Civil Engineering MIST, Dhaka	Member (Ex-Officio)

Department of Civil Engineering, MIST, Dhaka

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DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety and it (fully or partially) has not been submitted for any degree or diploma in any university or institute previously. Further I certify that all the intellectual content of this thesis is the product of my own work and all the assistance received in preparing this thesis and sources have been acknowledged and cited in the reference section.

Md Ferdous Ahmed
Student No. 0419110013

Department of Civil Engineering, MIST, Dhaka

ABSTRACT

CRASH SEVERITY MODELLING INVOLVING PUBLIC BUS CRASHES IN DHAKA CITY

This study attempts to identify the influencing factors for triggering public bus crash injury severity in Dhaka city where public buses alone were involved in 23 % of all the crashes. Though there are some descriptive-based works in Bangladesh pertinent to public bus safety, very few in-depth studies on the crash severities of public bus have been conducted; those are however, mostly based on an old crash data. Hence, utilizing the recent crash data (2017-2020) collected from the Accident Research Institute (ARI) of Bangladesh University of Engineering and Technology (BUET), the primary goal of this study is to discover the roadway and environment-related factors impacting the public bus crash severity in the context of Dhaka city.

A prominent way to deal with crash injury severity is by using statistical modelling techniques; the selection of these suitable methods often depends on the nature of data, especially the response variables. R software environment has been adopted to facilitate the analysis. In relation to the genre of police-reported public bus crash data, four different established models namely, Multinomial Logit (MNL), Ordered Logit (OL), Ordered Probit (OP) and Partial Proportional Odds (PPO) have been selected for the study. All of these severity models were then applied on this crash data to investigate public bus safety mechanism prevalent in Dhaka city.

The analysis showed that pedestrians, bicyclists and motorcyclists are the most vulnerable road user group (around 80%), as indicated by the all selected models. Lack of efficient police controlled traffic in all the places (in some cases, 0% fatal incidents in police-controlled areas), absence of dividers in two way roads (38.23% fatal vs 57.78% fatal where there are no dividers), over speeding, lack of necessary safety parameters as per the condition/geometry of roads etc. seemed to accelerate road traffic crashes. In addition, the severity models (i.e., MNL, OL, OP, and PPO) were evaluated in terms of relevant comparative parameters where MNL model is found to be more effective in terms of log-likelihood (-237) and PPO model fared better in terms of Akaike Information Criterion

(AIC_529) and Bayesian Information Criterion (BIC_616). The models were further evaluated on the significance of their predictors where collision type, junction type, movement, road class, road geometry, surface quality, surface type and time are found to be significant for triggering public bus related accidents in Dhaka city. Some viewpoints related to pedestrian facilities and roadway improvement (safety features) have been recommended for the decision makers for reducing both accident frequency and severity.

সারসংক্ষেপ

CRASH SEVERITY MODELLING INVOLVING PUBLIC BUS CRASHES IN DHAKA CITY

এই অনুসন্ধানমূলক রচনায় ঢাকা শহরে পাবলিক বাস সম্পর্কিত দূর্ঘটনার তীব্রতাকে প্রভাবিত করবার সম্ভাব্য কারনগুলি চিহ্নিতকরনের চেষ্টা করা হয়েছে, যেখানে সংঘটিত সমস্ত দূর্ঘটনার শতকরা ভাগই পাবলিক বাস সম্পর্কিত দূর্ঘটনা (২০২১ সালের সমীক্ষা অনুযায়ী)। যদিও বাংলাদেশে এ ধরনের যানবাহনের নিরাপত্তা কেন্দ্রিক কিছু বর্ণনাভিত্তিক কাজ থাকলেও, এর ফলে সৃষ্ট দূর্ঘটনা নিয়ে খুব কমই নিবিড় গবেষণাভিত্তিক কাজ হতে দেখা গিয়েছে। মূলতঃ এ সকল গবেষণার সিংহভাগই পুরনো তথ্য-উপাত্তের উপর ভিত্তি করে তৈরীকৃত। বাংলাদেশের প্রকৌশল ও প্রযুক্তি বিশ্ববিদ্যালয়ের (BUET) এক্সিডেন্ট রিসার্চ ইনস্টিটিউট (ARI) থেকে সংগৃহীত ট্রাফিক দূর্ঘটনার হালনাগাদকৃত তথ্য (২০১৭-২০২০) ব্যবহার করে, এই গবেষণার প্রাথমিক লক্ষ্য হলো পাবলিক বাস দূর্ঘটনা-বিষয়ক প্রভাবক রাস্তা এবং পরিবেশ-সম্পর্কিত কারণগুলি উদ্‌ঘাটন করা।

যানবাহন দূর্ঘটনা সম্পর্কিত ক্ষয়ক্ষতির ব্যা¡পকতা নির্ণয়ে পরিসংখ্যানগত মডেলের ব্যবহার একটি বহুল প্রচলিত ব্যবস্থা। তবে উপযুক্ত পদ্ধতি সমূহের নির্বাচন প্রায়শঃই উপাত্তের প্রকৃতির উপর নির্ভর করে; বিশেষ করে পরিবর্তনশীল প্রতিক্রিয়ার ধরণের উপর। মুলতঃ পুলিশ-প্রতিবেদিত পাবলিক বাস ক্রÉ¡শ ডাটা (Crash Data) এর উপর ভিত্তি করে চারটি ভিন্ন ভিন্ন প্রতিষ্ঠিত পরিসংখ্যানগত মডেল যেমন, মাল্টিনমিনাল লজিট (Multinomial Logit_MNL), অর্ডারড্ লজিট (Ordered Logit_OL), অর্ডারড্ প্রোবিট (Ordered Probit_OP), পারশিয়াল প্রপরশনাল অড্স (Partial Proportional Odds_PPO) গবেষণার জন্য নির্বাচন করা হয়েছে।

দূর্ঘটনা তীব্রতা নিরুপণে এ সমস্ত মডেলসমূহ পরবর্তীতে ঢাকা শহরের পাবলিক বাস সম্পর্কিত দূর্ঘটনার উপাত্তের উপর প্রয়োগ করা হয়েছিল। উল্লেখ্য যে, বিশ্লেষণের সুবিধার্থে সমগ্র গবেষণায় 'আর' (R) সফট্ওয়্যার ব্যবüত হয়েছে।

বিশ্লেষণে দেখা যায় যে পথচারী, সাইকেল চালক এবং মোটরসাইকেল চালকরা হলো সবচেয়ে ঝুঁকিপূর্ণ রাস্তা ব্যবহারকারী গোষ্ঠী (প্রায় ৮০%), যা চারটি মডেল/প্রতিমান দ্বারাই নির্দেশিত। দক্ষ পুলিশ নিয়ন্ত্রিত ট্রাফিক ব্যবস্থাপনার অভাব (কিছু ক্ষেত্রে, পুলিশ-নিয়ন্ত্রিত এলাকায় ০% মারাত্মক দূর্ঘটনা), দ্বিমুখী রাস্তায় ডিভাইডারের অনুপস্থিতি (৩৮.২৩% মারাত্মক বনাম ৫৭.৭৮% মারাত্মক, যেখানে কোনও ডিভাইডার নেই), অতিরিক্ত গতি, রাস্তার প্রকৃতি অনুযায়ী প্রয়োজনীয় ট্রাফিক নিরাপত্তা ব্যবস্থাদির অপ্রতুলতা ইত্যাদির কারণে রাস্তায় প্রতিনিয়ত দূর্ঘটনা ঘটছে। এক্ষেত্রে, তীব্রতা প্রতিমানগুলো (MNL, OL, OP এবং PPO) তুলনামূলক পরিমিতিগুলির প্রেক্ষিতে মুল্যায়ন করা হয়েছিল, যেখানে এমএনএল (MNL) মডেলটি লগ-সম্ভাব্যতা (-২৩৭) অনুযায়ী এবং পিপিও (PPO) মডেলটি এআইসি (AIC_৫২৯) এবং বিআইসি (BIC_৬১৬) পরিমিতির ক্ষেত্রে অধিকতর কার্যকরী মডেল হিসেবে পরিগণিত হয়েছে। এছাড়াও, প্রতিমানগুলো হতে প্রাপ্ত ফলাফল (রাস্তা ও পরিবেশ বিষয়ক) এর প্রেক্ষিতে দেখা যায় যে সংঘর্ষের ধরণ, রাস্তার সংযোগস্থল এর ধরণ, চলাচল, রাস্তার শ্রেণী, রাস্তার জ্যামিতি, পৃষ্ঠের গুণমান, পৃষ্ঠের ধরণ এবং সময়, ঢাকা শহরে পাবলিক বাস সম্পর্কিত দূর্ঘটনা সংঘটনের ক্ষেত্রে প্রভাবক হিসাবে তাvপর্যপূর্ণ ভূমিকা পালন করে। পরিশেষে, বিষেয়োক্ত গবেষণায় ঢাকা শহরে পাবলিক বাস এর দূর্ঘটনা পুনরাবৃত্তির হার এবং তীব্রতা, উভয়ই করানোর জন্য পথচারী সুবিধা বৃদ্ধিসহ রাস্তার নিরাপত্তা বৈশিষ্ট্যের উন্নয়ন সম্পর্কিত কিছু দৃষ্টিভঙ্গি সুপারিশ

করা হয়েছে।

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LIST OF MAIN NOTATION

ADU	Accident Data Unit
AIC	Akaike Information Criterion
ARF	Accident Report Form
ARI	Accident Research Institute
BIC	Bayesian Information Criterion
BRTA	Bangladesh Road Transport Authority
BUET	Bangladesh University of Engineering and
DMP	Dhaka Metropolitan Police
FIR	First Information Report
GDP	Gross Domestic Product
HQ	Headquarters
HRL	Hazardous Road Locations
IDC	Institutional Development Component
MAAP	Microcomputer Accident Analysis Package
MNL	Multinomial Logit
MS	Microsoft
OL	Ordered Logit
OP	Ordered Probit
PDO	Property Damage Only
PPO	Partial Proportional Odds
RHD	Roads and Highway Department
RTI	Road Traffic Injury
RUM	Road User Movement
WHO	World Health Organization

CHAPTER 1
INTRODUCTION

1.1 Background and Motivation

Every society's social and economic progress is largely dependent on its transportation system. It plays a major role in determining our way of life and making up a sizeable portion of the national economy. Unfortunately, in recent years, due to the rapid urbanization process, high rates of vehicle and population growth and that of increased levels of mobility, inadequate transportation facilities and policies, a varied traffic mix with an overabundance of non-motorized vehicles, the absence of a dependable public and mass transportation system, and inadequate traffic management techniques have resulted in substantial road crash problems.

The economic and social distress caused by road crashes is a fundamental concern for traffic safety. As per the report of World Health Organization (WHO, 2018), global road traffic incidents cause approximately 1.35 million fatal injuries and up to 50 million non-fatal injuries per year. Every day, around 3,700 individuals pass away on world's highways. Over 90% of traffic fatalities occur in low and middle-income nations, claiming an economic loss of up to 5% of GDP (WHO, 2015). Same report also states that it is affecting about 3% of the world's GDP as a whole. In comparison to high-income countries (8.3 deaths per 100,000 population), low-income countries have a 03 times higher rate of traffic fatalities (27.5 deaths per 100,000 people). Approximately 2.5% of all deaths across all age categories are caused by traffic injuries, placing them 8th among the world's major causes of death. Road fatalities are predicted to increase to the 5th greatest cause of death by 2030, resulting in an estimated 2.4 million fatalities annually, unless quick action is taken (RHD, 2018).

Low and middle-income nations bear a disproportionately heavy economic burden from road accidents. The most recent cost estimate is that road traffic injuries cost USD 518 billion globally and USD $65 billion in low and middle-income countries each year, exceeding the whole amount of development aid received by these nations (WHO, 2018). The global epidemic of traffic injuries is still spreading throughout most of the world, despite recent stabilization or declines in the number of road traffic fatalities in many high-income nations. This is basically due to the fact that there were no decreases in the number of traffic fatalities in any low-income nation from 2013 to 2016.

Bangladesh has the highest population density in the world; as a result, it is essential to comprehend its roadway situation in order to create a transport system that is both efficient and safe. The main motorized transportation network, which consists of the National, Regional, and Zilla Highways, is maintained by RHD. RHD covers a total of 21,302 km of road network, of which 3813 km (18%) are national, 4247 km (20%) are regional, and 13242 km (62%) are Zilla highways in 2017. The number of motorized vehicles registered with the BRTA that are currently using this network is 2,984,200, which was found to be 737,400 in 2004-2005. (RHD, 2018).

According to a statistic based on data from 183 nations, Bangladesh is rated 106th in the world for having the most fatal road accidents. According to police statistics from 2021, over 4,000 people die and many more sustain major injuries on Bangladesh's roads each year ; currently holding one of the highest fatality rates (60 fatalities per 10,000 vehicles) worldwide. In the first eight months of 2021, there were 3,701 road incidents that resulted in 3,502 fatalities and 3,479 injuries. In Bangladesh, there were 4,891 traffic incidents in 2020 that resulted in 6,686 fatalities and 8,600 injuries, according to Jari Kalyan Samiti 2020's annual road accident monitoring report. This indicates that 18 persons perished in traffic accidents nationwide on an average each day. The yearly survey found that while there were 6.78% more accidents on regional highways in 2020 than in 2019, less accidents occurred on national highways, 0.16% at railroad crossings, and 2.19% on feeder roads.

The state of Bangladesh's roads is painted in a depressing light by international organizations. According to World Bank research (WB Report, 2019), Bangladesh, which only has 0.5 % of the world's vehicles, lost over 25,000 lives on roads in 2019. The research was included in a World Bank paper from 2019 titled "Guide for Road Safety Opportunities and Challenges: Low and Middle-Income Countries Country Profiles." This indicates that 15 persons pass away in the nation's traffic accidents and other occurrences for every 01 lakh people. Road traffic accidents are also the 7th leading cause of death in Bangladesh. According to WB study, individuals between the ages of 15 and 64 are responsible for 67% of road crash fatalities and injuries. Additionally, the age range of 15 to 49 years old has the highest death rate, and the male to female fatality ratio is 5:1. The report estimates that the cost of traffic accidents and serious injuries is 5.3% of Bangladesh's GDP. According to the World Bank, 3, 74,310 major injuries occurred in Bangladesh in 2019. The cost of injuries and fatalities totaled around $11,630 million. According to World Bank data, Pakistan had the greatest rate of road accident-related mortality in 2016, with 27,582 deaths, while the Maldives had the lowest rate, with 04 deaths per year.

The most vulnerable road users are pedestrians, bicyclists, motorcyclists, and people utilizing informal transportation, such as bus and truck passengers, who account for over 80% of all traffic deaths. According to Police Statistics 2021, about 34% of total road accidents occur in the city of Dhaka, of which 23% are public bus crashes. Modal share of vehicles say that bus (23%), truck (26%), micro bus (3%), cycle (3%), rickshaw/van (4%), vutvuti (6%), bike (14%), auto rickshaw (9%), private car (4%), and others (8%) are the vehicles that were most frequently involved in these collisions. Compared to the metropolitan areas, Bangladesh's rural areas record a higher number of RTI fatalities (Ul Baset *et al.*, 2017) According to research, 70% of traffic accidents happen on rural roads, including rural stretches of major highways. Nearly 80% of fatalities include vulnerable road users (i.e., pedestrians, bicyclists, and motorcyclists). Pedestrian-vehicle collisions are the main issue with notable involvement of buses and trucks. According to statistics, pedestrians can account for up to 62% of fatalities in urban vehicle crashes, and in Dhaka city, they account for around 70%. Of all the recorded accidents, 50% occurred on the state and regional highways. Nearly 40% of those accidents are concentrated on around 2% of the highway network; these parts are known as Hazardous Road Locations (HRLs). Approximately 2.5% of accidents that are reported happen on bridges and culverts (Mahmud and Hoque, 2011).

Nearly 10% of pedestrian accidents are caused by other accident/collision categories, suggesting that pedestrians may not only be the victims of accidents but also a contributing component in some of them. Urban dividers have been found to be quite successful in reducing fatal pedestrian accidents (38.23% fatal vs. 57.78% fatal, where there are no dividers). It has been determined that traffic control systems, particularly police-controlled traffic control systems in urban areas, are effective in lowering the number of fatal pedestrian accidents (in some circumstances, to 0% fatal incidences). It has been established that geometric intersections without police-managed traffic control systems are a contributing factor in deadly pedestrian accidents.

Compared to other types of geometric sections (such as curve only, slope, curve plus slope and crest), straight and level roadways have produced more double vehicle deadly accidents (more than 80% of incidents are fatal). The latter part of the previous finding worsened when the sections involved head-on, right-angle, overturn, hit an object in the road, and hit animal collisions (76.22% fatal); or occurred on national and regional highways or feeder roads (71% fatal); or during dawn/dusk and night (unlit) condition (90.91% fatal); or in daylight or night (lit) condition but without any centerline marking traffic control system (75.21% fatal).

85.29% of fatal single-vehicle crashes occurred in head-on, right angle, side swipe, hit object in the road, and hit object off-road collision types connected to curve only, slope only, and curve and slope geometric parts of the roads. 87.88% of fatal single-vehicle crashes were caused by poor lighting conditions at dawn, dusk, and at night (when it was not lit). Paradoxically, in the daytime and at night (lit), 86.67% of fatal single-vehicle crashes have occurred on brick and earthen road surfaces. Contrarily, single-vehicle fatalities have decreased on sealed surfaces even when there is rain (58.82% of crashes are not lethal). 94.74% of fatal single-vehicle crashes have occurred on roads with wet or flooded surface conditions. However, one-way highways with dry and muddy surfaces sometimes resulted in fatal instances (20%), as always perceived. Whereas, in case of two-way roads, it accounts for 86.54 % of the fatal single-vehicle accidents.

Bangladesh currently has a police-reported accident database only. There isn't yet a hospital or insurance-based accident database. The Accident Research Institute (ARI), BUET is continuing its efforts to create a database of accidents based on newspaper reports. However, the newspapers have significant reporting errors by spotlighting only to the serious fatal accidents occurring in the immediate vicinity of growing hubs. Injury accidents or accidents in isolated places are hardly ever mentioned in newspaper stories. Even the quality of newspaper reporting is not particularly noteworthy or elaborated for fact-finding, analysis, and study. For thorough accident analysis and qualitative study, the police-reported accident database is also insufficient and inadequate. To decrease underreporting and to maintain and enhance database quality, many independent databases are required.

Given the severity of the issues, Bangladesh is experiencing noteworthy constraints at all levels, and safety programs related to promoting traffic safety are still in their infancy. In

Bangladesh, the works pertaining to public bus crashes have remained in limited form and are mostly descriptive-based. Dhaka being the city of diverse traffic, the scenario is somewhat more aggravating. However, few comprehensive research on the collision severity of public buses have been done, despite the fact that these crashes have cemented a permanent place in the electronic and print media. There were also various attempts to study public transportation in the late 1990s and early 2000s, but they tended to be either literature-based, focused on specific buses or trucks, or concerned with the behavior of public transportation drivers. Therefore, the goal of this study is to determine the roadway and environment-related factors influencing the severity of crashes involving public buses with comparatively newer set of crash data (2017-2020) for Dhaka City using alternative severity models namely; multinomial logit (MNL), ordered logit (OL), ordered probit (OP) and partial proportional odds (PPO), as well as to identify the model that will work better in situations where the data is incomplete, such as Bangladesh.

1.2 Objectives of the Study

Utilizing traffic accident data (2017–2020) from ARI, BUET, the primary goal of this study is to discover the influencing factors triggering public bus crash injury severity. In the context of Dhaka city, the study specifically examined the viability of discrete-outcome probabilistic models. The precise objectives of this research are:

a) To identify significant independent variables impacting public bus crash severity outcomes for Dhaka city (i.e., fatal, grievous, simple injury, and motor collision).

b) To carry out an in-depth analysis (parameter estimation, model comparison) on the proposed methods (MNL, OL, OP, PPO) using the recent crash data of Dhaka city and recommend the most reliable/robust one**.**

c) To recommend pragmatic measures for necessary safety enhancement.

1.3 Scope of the Study

In Bangladesh, public buses are frequently at blame for tragic collisions. According to data from BRTA 2020, there are 3,419,884 registered vehicles in the nation as of March 2018, of which 72,336 of those are designated as ‘Public Buses’, which can hardly be ignored. Moreover, the involvement of public buses in severe traffic crashes is also noteworthy.

Given the seriousness of the severity of public bus crash injuries, this study examines the correlation between a number of predictors (namely, geometric and environmental parameters) and the severity of crash injuries caused by public bus crashes. This thesis does not address the severity of injuries brought on by truck, light motor vehicle, or non-motorized vehicle crashes. Additionally, the analysis of this study excludes a number of variables, such as driver attributes, vehicle-related features, pedestrian features, etc.

1.4 Thesis Outline

This study has been organized into six chapters.

Chapter 1: Introduction. This chapter contains the background and motivation, objectives as well as scope of the study.

Chapter 2: Literature Review. In the context of Bangladesh and the wider world, this chapter evaluates the literary works that are pertinent to and related to the main idea of the research. A summary of public vehicles, accident severity categories, and other topics are also provided in this chapter**.**

Chapter 3: Research Methodology. The framework of the mathematical models used in this thesis is described in this chapter. It also explains the cross-tabulation procedure and a comparative study on the models that were obtained.

Chapter 4: Public Bus Safety Status in Dhaka City. This chapter provides a brief discussion on the public bus safety status in Dhaka city. It also provides an overview of Bangladesh's traffic accident database system. Additionally, this chapter includes graphical depictions of crash data for public buses in Dhaka city.

Chapter 5: Data Analysis and Model Selection. This chapter provides a framework for the in-depth evaluation and interpretation of findings from discrete outcome-based models. The validation of acceptable approaches in relation to models suitable for Bangladesh is also included in this chapter.

Chapter 6: Conclusion. This chapter presents the findings and policy implications of this thesis along with its limitations and future scope.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

The fact that road safety is a problem on a global scale, has inspired researchers and other professionals to take the required actions with a view to promoting safety every now and then. The goal of this study is to pinpoint the geometric and environment-related variables that influence the severity of public bus crashes in a developing nation like Bangladesh, especially in the context of Dhaka city. The current chapter begins by identifying the collision severity categories and defining "Public Bus" in accordance with RHD and BRTA. Following that, it compiles the pertinent literatures already in existence on the severity of public bus crashes, conducted to extract significant variables by using statistical models, and so performs a full evaluation on the goal, directions, and advancements made in this crucial research subject.

2.2 Illustration of the Related Terms

2.2.1 Public Bus

Roads and Highway Department (RHD) and Bangladesh Road Transport Authority are typically in charge of classifying automobiles in Bangladesh (BRTA). The following list of vehicles related to this work is organized chronologically based on the report supplied by (RHD, 2017).

Large Bus: Large buses are those with more than 40 seats and a chassis longer than 36 feet, according to RHD. Air-Conditioned, Chair Class, and Ordinary Large Buses are the three subcategories of large buses. Previously, Hino (Japan) and Tata (India) jointly controlled 88% of the large bus market. With a combined contribution of 41%, Tata is now in the lead with respect to the current situation. In Bangladesh, the air-conditioned bus models that connect the major cities include Hino, Volvo, Scania, Hyundai Universe, etc.

Mini Bus: Minibuses are vehicles with a seating capacity of 16 to 39 passengers and a chassis less than 36 feet. Tata, Isuzu, and Mitsubishi are the three main manufacturers of minibuses. Tata now holds a 35% market share for minibuses, making it popular.

Table 2-1: RHD Public Bus Categories (Source: RHD, 2017)

RHD Category	Description
Large Bus	>40 seats and >36 feet chassis
Mini Bus	16-39 seats and <36 feet chassis

2.2.2 Crash Severity Type

It is determined by the severity of the injuries a person (or people) involved in a traffic collision has experienced. According to Bangladesh Police's First Information Report (FIR) (see Appendix A, B, and C), there are primarily four types of accident severity:

Fatal Accident: A fatal accident is one that results in the death of one or more accident victims within 30 days of the commencement of the accident.

Grievous Accident: This kind of accident causes injury to the victims and necessitates their hospital admission without resulting in any death related issues.

Simple Injury Accident: This accident includes only minor injury, and as such, can be healed overnight.

Motor Collision: The term "motor collision" refers to the kind of accident that causes damage to the automobiles or other types of personal property.

2.3 Public Bus Pertinent Studies

2.3.1 National Studies

The interaction of crash severity with public buses in Bangladesh has only been the subject of a very small number of publicly accessible studies. The majority of the research done so far in Bangladesh has been examined based on straightforward statistics that illustrate the implications, limitations, and demands of the corrective actions taken to address the safety issue (Mahmud and Hoque, 2011). Studies have also been conducted to assess accident frequency of buses in order to determine the best safety precautions (Ahsan, Keya and Raihan, 2012). The works till now have helped the government in defining a holistic approach to overcome this severe problem, which however, fall short of the desired standard. The important research involving public buses are covered below:

In 2007, Hoque, Khondaker, and Hoque conducted a research on the driving behaviors and attitudes of heavy vehicle operators toward traffic safety. Through the use of a thorough questionnaire survey, an effort was made to understand the general profile, attitudinal, and behavioral characteristics of heavy vehicle drivers. The survey consisted of Ninety-nine questions, which were broken up into seven categories. The questionnaire focused on drivers' knowledge of road safety as well as their habits and viewpoints. The random sample approach was applied for sampling purposes. Five hundred drivers were sampled for the poll, comprising 279 bus and 221 truck drivers. The sample group was evenly divided across various bus and truck terminals, and it also made an effort to cover all significant national corridors spread across the nation from July 2003 to March 2004. In this study, drivers' knowledge of traffic control devices and their degree of proficiency behind the wheel in a variety of scenarios anticipated to result in auto accidents were also evaluated. The results of the study were used to gauge the degree of drivers' involvement in crashes and to create practical, workable, and efficient accident prevention strategies.

Anjuman et al. (2013) focused on the involvement of heavy vehicles in traffic incidents in order to portray the overall state of road safety in Bangladesh. According to their research, heavier vehicles like trucks and buses account for about 35 % and 29% of all fatalities in traffic accidents respectively. These vehicles were disproportionately involved in pedestrian collisions, making up around 68% (bus 38%, trucks 30%) of all pedestrian collisions and 80% of pedestrian fatalities. In heavy vehicle accidents, variables like the type of road, composition of vehicles, human factors, environmental factors, and the total number of vehicles involved were anticipated to play a considerably more significant influence in boosting injury severity. The potential remedies to this situation's perpetual collapse were also covered in this paper. It presented a preliminary investigation into the role of heavy vehicle drivers in multiple vehicle accidents and road safety. For a thorough grasp of the issue, the authors also suggested in-depth studies and investigations.

The significant factors affecting the severity of bus crashes in Dhaka, Bangladesh, were determined by Barua and Tay (2011). The authors used data from 1998 to 2005 to apply the ordered probit (OP) model. According to data from the Micro-Computer Accident Analysis Package (MAAP) software, Dhaka city accounted for 41% of all urban transit bus crashes. The outcomes of the analysis can be interpreted in the following ways: an upward trend in crashes involving transit buses over time, weekdays generated a high number of serious crashes, the majority of crashes involved two vehicles, although single-vehicle accidents were more serious, hit-pedestrian crashes were the most serious crash type, and the police control aided with signalized intersections reduced the chance of serious injuries.

2.3.2 International Studies

As a result of the quick, export-driven economic expansion, there is a noticeable increase in heavy vehicle (i.e., public bus, as well as truck) transportation across the road network in both high-income countries as well as many emerging and newly industrialized nations. For instance, China is observing an annual growth of 466,000 heavy vehicles (such as trucks and public buses) on its roadways. As such, the contribution of public bus crashes make up a sizable portion of fatal traffic accidents in China. In Australia, crashes involving heavy vehicles (such as trucks and public buses) account for up to 20% of all fatal road crashes, whereas in the USA, heavy vehicle crashes account for about 15% (Anderson and Hernandez, 2017). Similar rates are also reported in the EU member states. There is some urgency to better understand the factors related with this vocation given the high crash rates and rising number of public buses (i.e., large vehicles) on the road network (Anderson and Hernandez, 2017). The following discussion includes a few studies that have been done on public buses in various parts of the world:

Elvik (2002) presented a study on the impact of technical inspections of heavy vehicles (trucks and buses) during the period 1985–1997 in Norway on accidents. The effects of technical inspections were estimated using multiple regression analysis. The number of heavy vehicles involved in injury accidents may rise by 5–10% if inspections are eliminated; conversely, if inspections are increased by 100%, the number of accidents falls by a comparable amount. Although the study has a number of flaws; its findings are comparable with those of the previous studies that have examined the impact of technical flaws in heavy trucks on accidents and the remedies used to fix them.

Mooren et al. (2014) published a paper which reviews the literature on safety management interventions that have been successful in reducing the severity of injuries in occupational health and safety (OHS) and road safety, and evaluated their applicability in reducing crash and injury severity in heavy vehicular (trucks and buses) transport. Safety training, management commitment, scheduling or travel planning, size of organization or freight type, worker participation, incentives, and safety or return to work rules were among the operational and management traits linked to lower collision and injury risk. Risk analysis and corrective actions, prior safety violations, crashes or incidents, vehicle conditions or physical work environment, vehicle technologies, recruitment and retention, pay and remuneration systems, accreditation for safety or quality management, communications/support, financial performance, and worker characteristics and attitudes were other factors linked to lower incident and injury rates. The review also emphasized the gaps in the literature and suggested additional research.

Assemi and Hickman (2018) used partial least squares path modeling (PLS-PM) to determine how frequently heavy vehicles are inspected, what factors contribute to crashes, and how severe the crashes are. Using information from periodic heavy vehicle (trucks and bus) inspections and heavy vehicle (trucks and bus) collisions in Queensland, Australia, from 2011 to 2013, a research model was proposed and evaluated. In the primary vehicle's overall damage, primary vehicle casualties, other involved parties' overall damage, and other involved parties' casualties, the results of the model showed variations of 12.9%, 21.1%, 72.4%, and 11.5%, respectively.

Feng et al. (2016) investigated the risk variables associated with fatal bus accident injuries suffered by various types of drivers. Data that was recovered from the USA's Bus Involved in Fatal Accidents (BIFA) database for the years 2006–2010 was subjected to OL specifications. The K-means approach was used to divide drivers into three groups; with 425, 302, and 653 drivers in each cluster, respectively. The results showed that the middle-aged drivers with a history of traffic violations are "the safest ones" (i.e., they are less likely to be involved in more serious accidents), while the young and elderly drivers with a history of traffic violations are "the riskiest ones" (i.e., they are more likely to be involved in more serious accidents), and drivers without a history of traffic violations fall somewhere in between.

2.4 Model Pertinent Studies

Researchers frequently employ statistical methods to gauge the seriousness of accident injuries. In some studies, (Shankar and Mannering, 1996; Carson and Mannering, 2001; Ulfarsson and Mannering, 2004; Khorashadi et al., 2005; Kim et al., 2007; Tay et al., 2011), multinomial logit (MNL) models with multiple levels of injury severity were used, whereas ordered probability models (viz. OL, OP, etc.) were used to account for the ordinal nature of the crash (O’Donnell and Connor, 1996; Kockelman and Kweon, 2002; Abdel-Aty, 2003; Garrido et al., 2014; Feng et al., 2016). On the other hand, these techniques have their own set of restrictions. To get around the limitations of conventional (i.e., nominal and ordered) probability models, Peterson and Harrell (1990) proposed the partial proportional odds (PPO) model. This model takes into account the ordinal nature of traffic crash severity and permits some independent variables to have different impacts across crash severity levels. Due to its distinct combination of flexibility and data constraints, the PPO model has been used in a number of research (Wang and Abdel-Aty, 2008; Wang, Chen, and Lu, 2009; Soon, 2010; Sasidharan and Menéndez, 2014; Li and Fan, 2019). This strategy, though, is beyond the purview of this case.

The work on a comparison study of paradigms that behave differently in various contexts is also revealed in a research (Mooradian et al., 2013; Zong, Xu and Zhang, 2013; Iranitalab and Khattak, 2017). The majority of injury severity analyses in recent years have relied on extensions of ordered response models (Generalized Ordered Logit/Probit, Hierarchical Ordered Logit, Bayesian Spatial Generalized Ordered Logit/Probit, Heteroskedastic Ordered Probit) that take into account for different specification limitations (Quddus, Wang and Ison, 2010; Lemp, Kockelman and Unnikrishnan, 2011; Wang, Yin and Zeng, 2019). In certain review publications, methodological approaches for assessing the seriousness of accident injuries were also highlighted (Savolainen et al., 2011; Mooren et al., 2014).

2.4.1 Multinomial Logit (MNL)

Shankar and Mannering (1996) used a multinomial logit (MNL) model to predict the severity of motorcycle rider crashes based on crash frequency. The five-year state-wide study of single-vehicle motorbike crashes in Washington, USA, provided the crash data. Five levels of severity were examined by the authors: death, serious harm, obvious injury, possible injury, and property damage alone (PDO). The results show that the use of a helmet in a fixed-object collision is ineffective because this situation increases the risk of fatality. Overall, the multinomial logit model performed well in identifying the variables affecting the severity of motorcycle crashes.

The usefulness of ice warning signs in lowering the quantity and severity of accidents was examined by Carson and Mannering (2001) in Washington State, USA. The authors specifically examined crash severity using the MNL specification. The information showed that a crash's severity was unaffected by an ice warning sign's presence. On the other hand, truck tractors and semi-trailers were found to be a significant contributor to fatal collisions, and PDO occurrences were found to be more likely as the drivers' age grew.

Ulfarsson and Mannering (2004) used various multivariate MNL models to examine how male and female drivers differed in terms of accident severity in single- and two-vehicle collisions involving SUVs, minivans, pickup trucks, and passenger cars. The algorithms were created to calculate the likelihood of four severity outcomes: fatal harm, obvious injury, possible injury, and no injury (PDO). The results of the estimations showed that variables have a considerably different impact on the degree of damage in male and female drivers.

(Kim et al., 2007) used the MNL model to analyze the elements that affect how seriously an injured cyclist is hurt in a collision with a motor vehicle. Police-reported crash data from North Carolina, USA, from 1997 to 2002 served as the study's foundation. The authors listed a number of characteristics that had a significant effect on fatal injuries, including inclement weather, darkness without illumination, head-on incidents, truck involvement, cyclists aged 55 or older, and others. However, the probability of death increases by almost 16 times if the vehicle's speed just prior to the accident was more than 80.5 km/h.

Tay et al. (2011) used the MNL model in South Korea to identify the variables that influence the severity of pedestrian-vehicle collisions. The researchers discovered that, compared to minor incidents, fatal and serious collisions were associated with light-vehicle collisions, collisions involving intoxicated drivers, male or younger pedestrians, female or older pedestrians, and pedestrians struck in the centre of the road. On the other hand, the study also found that the drunk drivers are more likely to be involved in minor injury crashes than catastrophic damage crashes.

2.4.2 Ordered Logit (OL)

O'Donnell and Connor (1996) estimated two ordered paragons, specifically the ordered logit (OL) model and the ordered probit (OP) model with heteroscedasticity, to assess injury severities in traffic crashes in New South Wales, Australia. The results showed that the chance of serious injuries and fatalities is increased by vehicle speed, vehicle age, and victim age. According to the authors, factors such as seat position, blood alcohol content, gender, collision type, and vehicle type (especially light-duty vehicles) significantly affected the severe outcomes.

To examine the connection between crash severity and traffic congestion, Quddus, Wang, and Ison (2010) used ordered response models including the OL model, heterogeneous choice model (HCM), and generalized ordered logit (GOL) (partially restricted) models. These models work well for both disaggregate crash data and ordinal dependable variables. The results showed that the severity of collision injuries is not significantly affected by traffic congestion on London's M25 highway.

2.4.3 Others

Hutchinson (1986) estimated the seriousness of occupant injuries in a traffic collision using an OP model. Cross-tabulation was used to display the severity of injuries to the driver and front-seat passenger in four separate single-vehicle crashes. For that matter, the processed British accident data from 1962 to 1972 were used. According to the authors, passengers are more likely than drivers to sustain serious injuries in non-overturning collisions, but no difference was seen in overturning collisions.

Abdel-Aty (2003) examined factors affecting the severity of driver injury levels across several Central Florida sites using the OP model. He developed concepts for toll plazas, signalized intersections, and road segments. The results showed that the driver's age, gender, seat belt use, speed, point of impact, and crash type all have a higher chance of severe injury regardless of the occurrence site. However, there is a higher likelihood that the drivers will be hurt if the cars are using an Electronic Toll Collection system (E-Pass) at a toll plaza. The author carried out the same analysis using layered logit response models and multinomial logit response models. OP had a higher goodness-of-fit score than MNL, and although being more effective, NL was avoided because of its complexity.

Garrido et al. (2014) conducted research on the severity of injuries sustained by motor vehicle occupants in Portugal. The datasets were first examined for multicollinearity as part of the modeling strategy, and then the OP specification was used. Women are more likely than men to die in an automobile accident, yet the driver's seat is considered to be the safest position inside the car. Although the former experiences more accidents, it was also shown that urban areas experience less serious collisions than rural ones.

Wang, Chen, and Lu (2009) investigated and evaluated the factors that affect how serious injuries are at highway divergence zones. At 231 separate highway exit segments in the state of Florida, crash data and route statistics were gathered. Using Partial Proportional Odds (PPO) regression, which removes the constraint that all regression coefficients be the same across all output values and allows one or more regression coefficients to differ across outcome levels, the injury severity prediction models were developed. Injury severity at freeway to diverge areas was significantly influenced by the length of deceleration/ramp lanes, curve and grade at diverging areas, light and weather conditions, alcohol/drug involvement, heavy vehicle involvement, number of lanes on mainlines, ADT on mainlines, surface conditions, land type, and crash types. The study also found that injury severity at motorway diverge locations was not significantly impacted by exit ramp designs.

The Partial Proportional Odds (PPO) model was created by Mooradian et al. (2013) to bridge the gap between ordered and multinomial techniques without compromising their central tenets. PPO came out on top when the response models were contrasted in terms of model fit, covariate significance, and holdout prediction accuracy. On the other hand, it was demonstrated that the MNL model had the best average fit.

The PPO model was applied as a logistic regression model by Toran Pour et al. (2016) for pedestrian crashes at mid-blocks in the Melbourne Metropolitan Area. This study examined vehicle-pedestrian collisions in mid-blocks for the first time. Additionally, this model was also developed by taking into the account of different variables like the separation between crashes and public transit stations, average road gradient, and the numerous socioeconomic characteristics for the first time. The PPO model showed that the most significant parameters determining the severity of car-pedestrian crashes at mid-blocks are the speed limit, light condition, pedestrian age and gender, and vehicle type.

The parameters of road accident severity data and the most popular analytical approaches for analyzing such data were computed by Savolainen et al. in 2011. According to the authors, binary response models (such as binary logit, binary probit, etc.), ordinal discrete response models (such as OL, GOL, etc.), nominal multinomial discrete response models (such as MNL, NL, etc.), and some data mining techniques are among the discrete response paradigms that gave rise to the majority of modeling approaches.

Zeng et al. (2020) examined Bayesian network and Regression models for forecasting the seriousness of traffic accidents (i.e., OP model). The number of fatalities, injuries, and property damage were the officially recognized severity indicators. The authors came to the conclusion that Bayesian networks performed better than Regression models in terms of the mean absolute percentage error (MAPE) and hit-ratio. However, missing factors such as traffic circumstances and driver characteristics restricted the effort.

Wang, Chen, and Lu (2009) looked into the pertinent variables that predict the seriousness of driver injuries in rural non-interstate collisions in the state of New Mexico. The authors employed Bayesian inference to estimate the model using the hierarchically ordered logit (HOL) model. In contrast to heavy vehicle drivers, motorcycle riders, female drivers, elderly drivers, and the majority of accident types (such as head-on, rear-end, angle collision, overturn, fixed object, sideswipe, and other collision) were all significant in causing serious injury. An OL model was also generated, although it was less accurate in terms of interpretation than the H-OL model.

Iranitalab and Khattak (2017) investigated four statistical and machine learning methods for forecasting traffic crash severity: the MNL model, Nearest Neighbor Classification (NNC), Support Vector Machines (SVM), and Random Forests (RF). As part of their investigation into the effects of data clustering techniques like K-means Clustering (KC) and Latent Class Clustering, the authors also developed a crash costs-based method for evaluating different prediction algorithms (LCC). MNL, NNC, and RF all performed better when using clustering techniques, but NNC had the best prediction performance.

A Bayesian spatial GOL model with conditional autoregressive priors was constructed by Zeng et al. (2020) to examine the severity of Kaiyang road crashes in China. Using Bayesian inference, the proposed model was contrasted against a typical G-OL model, and the former was found to be superior. Major crashes rose as a result of a variety of reasons, including the summer season, vertical gradients, angle collisions, and others. Professional drivers' significant representation in the dataset as intercity coach drivers can be used to explain their role in elevating the likelihood of fatal accident.

2.5 Summary

Public bus accidents are a problem for both industrialized and developing nations. In many developed nations across the world, discrete outcome models (MNL, PPO, OL, OP, GOL, etc.) have shown to be efficient and reliable in determining the severity of collision injuries.

On the contrary, in many underdeveloped countries like Bangladesh, efforts to address this type of challenge are mostly based on descriptive analyses, and often impeded by the incompleteness of accident data. As a result, it is past due for Bangladesh to employ more cutting-edge approaches supported with modern technologies, such as discrete outcome models, to provide an effective solution to this serious issue.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the methodology for creating mathematical models that make it easier to assess the seriousness of a public bus crash. For poor nations like Bangladesh, the process for identifying the underlying high impact characteristics determining crash severity is hazy. This issue is primarily brought on by poor crash data recording. As a result, basic probabilistic methods have been applied as the main strategy in this research to address the limitation of data under-reporting.

3.2 Methodological Flow of the Study

This work has been carried out analytically which consists of three crucial tasks: comprehending the current state of traffic safety in Bangladesh as well as Dhaka city, using probabilistic methods to delve into the crash data for some unusual and far-reaching outcomes, and choosing the best methodology through comparative study in the context of this country. The first task includes simple cross-tabulation in MS Excel utilizing accident data from Accident Research Institute (ARI). The second job, which is the most important portion of the study, used discrete response models to evaluate the data in the R programming environment, including the multinomial logit (MNL) model, ordered logit (OL) model, ordered probit (OP), and partial proportional odds (PPO) model. Finally, an appropriate model that best addresses the data crises in the context of Bangladesh was chosen based on fit adequacy and comparison of variables. The subsequent sections give a quick overview of the relevant steps in order.

3.3 Cross-Tabulation

Cross-tabulation, commonly referred to as a contingency table, is a statistical method for analyzing categorical data that are mutually exclusive. This method groups information about the variables to evaluate the relationship between them and also shows the pattern of change in the variable groups. Cross-tabulation makes it possible to investigate data at a more granular level, which makes it easier to interpret and offers deeper insights. The convenience of using data of various sorts is the main benefit of contingency table analysis (viz., nominal, ordinal, interval, and ratio). In this study, a straightforward cross-tabulation will be used to comprehend the dataset that represents the severity of public crashes. Most studies on the safety of public buses have used it as the basis of analysis.

3.4 Discrete Outcome Models

Since several practical judgments are made using this information, discrete data frequently play an important role in traffic engineering. Theoretically, these data are divided into two categories: those describing discrete outcomes of a physical event and those requiring behavioral choice. Discrete models can be traced back to either from economic theory or from simple probabilistic theory based on physical and behavioral phenomena, respectively. Most road traffic incidents are physical events that produce distinct results. The use of probabilistic models to forecast and evaluate crash severity for categorical response variables was therefore recommended by Mooradian et al. (2013). However, the examination of accident data has its own relevance for economic theory. Econometric models were adopted into some of the older crash severity calculation techniques (Mooradian et al., 2013).

Traffic collisions produce discrete injury severity outcomes, which are often arranged from the worst crash (death) to the least bad crash (motor collision). In Bangladesh, public bus accidents are typically categorized according to their severity as follows: (a) motor collision, (b) simple injury accident, (c) grievous accident, and (d) fatal accident. In order to draw the relationship between crash severity levels, ordered probability models, such as the ordered logit (OL) and the ordered probit (OP) are often used for convenience (Hutchinson, 1986; O'Donnell and Connor, 1996; Kockelman and Kweon, 2002; Iranitalab and Khattak, 2017; Quddus, Wang, and Ison, 2010; Abdel-Aty, 2003; Yamamoto and Shankar, 2004; Lee and Abdel-Aty, 2005; Barua and Tay, 2011; Tay et al., 2011).

To provide for the non-monotonic effect of the independent variables on the dependent variable, models for nominal outcomes are frequently used with ordinal response variables. This method makes the assumption that damage severity levels are nominal or unordered. In contrast to proportion odds, unordered response models, such as the multinomial logit (MNL) model allow all model variables to have a different impact on each response level (Shankar and Mannering, 1996; Carson and Mannering, 2001; Ulfarsson and Mannering, 2004; Khorashadi et al., 2005; Savolainen et al., 2011; Kim et al., 2007; Mooradian et al., 2013). The estimation of parameters for ordered response variables using conventional unordered requirements may be impartial, particularly when data are lacking, according to Yamamoto, Hashiji, and Shankar (2008).

Partial Proportional Odds (PPO) model ignores the limitations provided by ordered response and multinomial models. The PPO is, in fact, an intermediate method bridging the gap between ordinal and MNL models (Sasidharan and Menéndez, 2014).

The discrete nature of response variable has motivated the use of MNL, OL, OP and PPO models, as the basis of analysis for this research work, which are briefed below:

3.4.1 Multinomial Logit (MNL) Model

3.4.1.1 Model Assumption

a) Assumes data are level specific i.e., each feature has a unit value for each level.

b) Ignores the sequential order of the levels of response variable.

c) Relies on the assumption of independence of irrelevant alternatives (IIA). For more details, see 3.4.1.5.

d) Disturbance term is assumed to be identically and independently distributed (IID) with type 1 extreme value distribution.

3.4.1.2 Mathematical Interpretation

The probability of observation n experiencing injury with severity outcome i can be written as,

$$P_n(i) = P(U_{ni} \geq U_{nI}), \forall I \neq i \tag{3.1}$$

where, $i =$ Crash severity outcomes: 1,2, … , I .

$U_{ni} =$ Function of covariates that determines the likelihood of severity i of observation n.

It is assumed that an individual usually endures the one severity type which maximizes U_{ni}. Using a linear-in-parameter form, such that,

$$U_{ni} = \beta_i X_n + \varepsilon_{ni} \tag{3.2}$$

Where, β_i = Vector of estimable parameters for injury outcome i.

X_n = Vector of exogenous explanatory variables.

ε_{ni} = Disturbance term accounting for the unobserved effects influencing injury severity i of individual n.

The unobserved term ε_{ni}'s is assumed to be independent from one severity level to another; The term $\beta_i X_n$ is the observable component of severity determination as the vector X_n is composed of measurable variables (e.g., roadway attributes at the location of accident n) (Shankar and Mannering, 1996).

By substituting Eq. 3.2 in Eq. 3.1, the former can be expressed as,

$$P_n(i) = P(\beta_i X_n + \varepsilon_{ni} \geq \beta_I X_n + \varepsilon_{nI}), \forall I \neq i \quad (3.3)$$

or,

$$P_n(i) = P(\beta_i X_n - \beta_I X_n \geq \varepsilon_{nI} - \varepsilon_{ni}), \forall I \neq i \quad (3.4)$$

Eq. 3.4 promotes the derivation of severity model assuming a distribution form for ε_{ni}. A natural choice would be the assumption of normally distributed disturbance term. However, normal distribution violates the desirable property of the disturbance term which states, the maximums of randomly drawn values from the distribution have the same distribution as the values from which they were drawn (Washington et al., 2011). A more common approach is to assume that the disturbance term εni, is an extreme value type 1 distribution (sometimes referred as Gumbel distribution), which simplifies crash severity modeling.

The probability density function (pdf) for the distribution is,

$$f(\varepsilon) = \eta \exp\big(-\eta(\varepsilon - \omega)\big) \exp\big(-\exp\big(-\eta(\varepsilon - \omega)\big)\big) \quad (3.5)$$

The cumulative distribution function (cdf) is,

$$F(\varepsilon) = exp\ (-exp\ (-\eta(\varepsilon - \omega))) \quad (3.6)$$

where, η = Positive scale parameter.

ω = Location parameter (mode).

Mean = (ω + $0.5772/\eta$).

Standard multinomial logit model can be derived from generalized extreme value (extreme value type 1) assumption such as (McFadden, 1981),

$$P_n(i) = \frac{exp[\beta_i X_n]}{\sum_{\forall I} exp\ [\beta_I X_n]} \tag{3.7}$$

Where, all terms are previously defined. Given this equation, vector of parameters, β's can be estimated using standard maximum likelihood (ML) methods. For a sample of N observations, the log-likelihood function is,

$$LL = \sum_{n=1}^{N} \left(\sum_{i=1}^{I} \delta_{ni}[\beta_i X_n - LN \sum_{\forall I} exp\ (\beta_I X_n)]\right) \tag{3.8}$$

where, $\delta_{ni} = 1$, if discrete outcome for observation n is i.

$\delta_{ni} = 0$, if otherwise.

Multinomial logit models are structurally related to logistic regression models; however, assumptions, estimation technique, and associated results vary among these models (Ulfarsson and Mannering, 2004).

3.4.1.3 Model Identification

The sum of probabilities of all observed outcomes I of an individual n, using Eq. 3.7, equals to 1. However, addition of new parameters generates the same probabilities of observed outcomes (Long, 1997). The model is hence, not identified, which can be clarified revising Eq. 3.7 as follows,

$$P_n(i) = \frac{exp[\beta_i X_n]}{\sum_{\forall I} exp\ [\beta_I X_n]} \times \frac{aX_n}{aX_n}$$

or,

$$P_n(i) = \frac{exp[(\beta_i + a) X_n]}{\sum_{\forall I} exp\ [(\beta_I + a) X_n]} \tag{3.9}$$

where, $\frac{aX_n}{aX_n} = 1$.

$a =$ Parameters that keeps the values of probabilities unchanged.

The original parameter β_i have been replaced by $(\beta_i + a)$ for outcome i, producing a new set of parameters.

The model is made identifiable by imposing constraints on the β's, such that for any $a \neq 0$ the constraints are violated (Long, 1997). To execute this restriction for multinomial logit model, one of the β's is made zero. Considering the outcomes having values such as, $i = 1, 2, \dots I$, the arbitrary choice is made as follows,

$$\beta_1 = 0$$

Hence, the probability equation of observed outcomes is expressed as,

$$P_n(i) = \frac{exp[\beta_i X_n]}{\sum \forall_I \, exp\,[\beta_I X_n]} \tag{3.10}$$

where, $\beta_1 = 0$ and all terms are predefined.

3.4.1.4 Elasticity Determination

The interpretation of model's parameters is a bit perplexing as these values cannot fully explore the effect of explanatory variables on outcome probabilities. The motivation of this situation is the dependency of marginal effect of a variable on all coefficients, rather than a single coefficient (Khorashadi et al., 2005). Elasticities are then calculated and used to assess the marginal effects as a cure to this complication. The prime task of elasticity is to compute the influence of specific variables on the outcome probabilities. In general, elasticity of each observation n is expressed as,

$$E_{x_{nk}}^{P_n(i)} = \frac{\partial P_n(i)}{\partial x_{nk}} \times \frac{x_{nk}}{P_n(i)} \tag{3.11}$$

where, E = Elasticity.

x_{nk} = Value of kth variable for observation n.

$P_n(i)$ = Probability of observation n experiencing severity outcome i.

Applying Eq. 3.11 to the multinomial logit formulation using Eq. 3.7 provides,

$$E_{x_{nk}}^{P_n(i)} = (1 - P_n(i))\beta_{ik} x_{nk} \tag{3.12}$$

where, β_{ik} = Estimable parameter for outcome i associated with variable x_{nk}.

Elasticity values can approximately be interpreted as the percent effect of x_{nk} on the probability of severity-level (i). If the observed elasticity value is less than 1%, the variable x_{nk} is said to be inelastic, and a 1% change in x_{nk} will have less than a 1% change in the selection probability of outcome i. However, if the elasticity observed, is more than 1%, then a 1% change in x_{nk} will have more than a 1% change in the selection probability of outcome i.

Eq. 3.11 is only valid for continuous explanatory variables such as, driver's age, and vehicle speed. For indicator variables (those taking on values of 0 and 1), direct pseudo-elasticity is calculated. The equation can be written as,

$$E_{x_{nk}}^{P_n(i)} = \frac{exp\,[\Delta(\beta_i X_n)] \sum_{\forall I} exp\,[\beta_{Ik} x_{nk}]}{exp\,[\Delta(\beta_i X_n)] \sum_{\forall I_n} exp\,[\beta_{Ik} x_{nk}] + \sum_{\forall I \neq I_n} exp\,[\beta_{Ik} x_{nk}]} - 1 \quad (3.13)$$

where, $I_n =$ Set of alternate with x_{nk} in the function determining the outcome.

$I =$ Set of all possible outcomes.

Pseudo-elasticity of a variable can be elucidated as the average percent change in the probability of a specific crash level when the variable is changed from 0 to 1. Hence, a measured pseudo-elasticity of 0.5 for a variable, x_{nk} in the fatal injury category of observation n signifies that the probability of fatal injury is increased, on average, by 50%, when the value of variable, where $x_{nk} = 0$, is changed from 0 to 1.

3.4.1.5 Model Limitations

This section describes about the specification errors resulting due to the violation of assumptions made to generate the multinomial logit model (MNL), for the analysis of sample data.

Independence of Irrelevant Alternatives (IIA): IIA in the MNL model simply refers to the independence of the ratio of probabilities of any two outcomes from the functions determining any other outcomes. This property is seemed to persist in the multinomial logit specifications, if all the outcomes share the same unobserved effects (materialized in the disturbance term), which eventually cancels out according to Eq. 3.4; however, the problem arises when some of the outcomes share unobserved effects, and the probability ratio is no longer independent (Ulfarsson and Mannering, 2004). This correlation problem (IIA violation) can be addressed with nested logit models.

The red bus-blue bus paradox is an excellent explanation to this situation. Let's consider, a commuter has two choices with same utility for commuting to college: an auto that is selected with $P_r(auto) = 1/2$ and a red bus with $P_r(red\ bus) = 1/2$. The odds of taking the auto over the red bus is$(1/2)/(1/2) = 1$. Now, suppose a new bus service is introduced in the region that is identical to the existing service, except the buses are painted blue. For validation IIA, multinomial logit predicts: $\mathrm{P_r}(\text{auto}) = 1/3$, $\mathrm{P_r}(\text{red bus}) = 1/3$, and $\mathrm{P_r}(\text{blue bus}) = 1/3$, so that, the odds of auto over red bus remains the same $(= (1/3)/(1/3) = 1)$. However, color cannot be the only reason of the shift of choice. Instead, the share of red bus $\mathrm{P_r}(\text{red bus}) = 1/2$ would split, resulting in: $\mathrm{P_r}(\text{auto}) = 1/2$, $\mathrm{P_r}(\text{red bus}) = 1/4$, and $\mathrm{P_r}(\text{blue bus}) = 1/4$. The novel ratio$(= (1/2)/(1/4) = 2 \neq 1)$, hence, infers the violation of IIA assumption.

Identically and Independently Distributed (IID): A major conjecture of the MNL model derivation is considering the independent, and identical distribution (IID) of the disturbance term, ε i.e., the variance of the disturbance is constant; however, an undesirable contradictory scenario results in inconsistent parameter estimates (Washington et al., 2011). Having said that, 'comfort' (unobserved) is considered a crucial disturbance influencer in the paragon of choice of mode of travel; let's assume, Personal vehicles (BMW, Toyota Premio, and Tata Nano), and MRT are the modes to use. Pondering the influencer, it can be deduced that variance of the disturbance term is bigger for personal vehicles than the disturbance term for MRT (Washington et al., 2011).

Omitted Variables: The crash reports often contain limited information resulting in an erroneous analysis of data. Elimination of relevant variables can lead to a specious estimation of coefficients, if such variables possess any significant connection with the other variables existing in the model, or the mean and variance of the omitted variables vary across severity outcomes (Washington et al., 2011; Savolainen et al., 2011).

Irrelevant Variables: Despite the fact that results are obtained using extraneous variables, efficiency of parameter estimates will be eluded concluding in a meaningless effort.

Endogeneity: The influence of injury-severity levels on the explanatory variables can arise estimation issues using the MNL model. Specifically, Carson and Mannering (2001) rationalized the endogenous nature of ice warning sign in relating it with ice- accident frequency. The authors elucidated that ice-accident frequency can potentially impact the presence of ice warning sign as it is a conventional exercise to place warning signs at accident spots. Hence, the analysis might put forth a fallacious result, showing signs only increases accident frequency, if the endogeneity is ignored (i.e., ice warning is considered an exogenous variable).

3.4.2 Ordered Logit (OL) Model

3.4.2.1 Model Assumption

a) Parallel Odds Assumption: According to the parallel odds assumption (also known as parallel lines assumption), the effect of an independent variable will be uniform across all levels of response variable i.e., the value of estimable coefficient β is same for all outcome levels i (Soon, 2010; Sasidharan and Menéndez, 2014). The fulfilment of the assumption thus conditions on the parallelism of the odds ratios across severity levels. A test devised by Brant (also known as Brant Test) is used to assess the validity of parallel odds assumption.

b) Disturbance term is assumed to be logistically distributed across observations.

c) Assumption is made considering homoscedastic nature of disturbance term (i.e., the variance of disturbance term cannot vary across observations).

d) The disturbance terms for different observations are assumed to be uncorrelated.

3.4.2.2 Mathematical Interpretation

Ordered logit model, also known as Proportional odds (PO) model, is usually defined in a latent (i.e., unobserved) variable framework. The general specification of each single equation model is,

$$z_n = \beta X_n + \varepsilon_n \tag{3.14}$$

where, $z_n =$ Latent continuous variable measuring the risk of injury faced by observation n in a crash.

$X_n = p \times 1$ vector of non-stochastic (i.e., non-random) explanatory variables measuring the attributes of observation n.

$\beta = p \times 1$ vector of parameters to be estimated.

$\varepsilon_n =$ Random disturbance term.

The error term is assumed to be logistically distributed across observations with mean$= 0$, and variance= $\pi^2/3$, which eventually results in an ordered logit model (Washington et al., 2011).

The probability density function (pdf) is,

$$\lambda(\varepsilon) = \frac{exp\ (\varepsilon)}{[1+exp\ (\varepsilon)]^2} \tag{3.15}$$

The cumulative density function (cdf) is,

$$\Lambda(\varepsilon) = \frac{exp\ (\varepsilon)}{[1+exp\ (\varepsilon)]} \tag{3.16}$$

The unknown parameter β is to be estimated; however, standard regression technique cannot be applied to Eq. 3.14, as dependent variable, z_n is unobserved (O'Donnell and Connor, 1996). Instead, the observed and coded discrete injury severity variable, y_n contained in the data is used, and a relation is drawn with the latent variable, z_n as follows:

$$y_n = \begin{cases} 1, & -\infty \leq z_n \leq \mu_1 & \textit{(Motor Collison)} \\ 2, & \mu_1 < z_n \leq \mu_2 & \textit{(Simple Injury Accident)} \\ 3, & \mu_2 < z_n \leq \mu_3 & \textit{(Grievous Accident)} \\ 4, & \mu_3 < z_n \leq \infty & \textit{(Fatal Accident)} \end{cases} \tag{3.17}$$

where, the threshold values μ_1, μ_2 and μ_3 are unknown estimable parameters. This implies that the probability of injury severity i sustained by observation n is the same as the probability that an unobserved variable z_n measuring injury risk, takes a value between two thresholds. The cumulative probability for a given crash n with injury severity levels i can be expressed as follows:

$$P(y_n \leq i) = \frac{exp[\mu_i - \beta X_n]}{1+exp\ [\mu_i - \beta X_n]} \tag{3.18}$$

where, y_n = Recorded crash injury severity for crash n.

i = Crash injury severity levels: 1, 2…, $I - 1$.

μ_i = Cut-off point for level i.

$X_n = p \times 1$ vector containing the values of all p predictor variables for crash n.

$\beta = p \times 1$ vector of estimable parameters associated with X_n.

The probabilities associated with the coded responses of an ordered logit model can be further shown as,

$$
\begin{aligned}
P_n(1) &= Pr\ (y_n = 1) = Pr\ (z_n \le \mu_1) = Pr\ (\beta X_n + \varepsilon_n \le \mu_1) \\
&= Pr\ (\varepsilon_n \le \mu_1 - \beta X_n) = \Lambda(\mu_1 - \beta X_n) \\
P_n(2) &= Pr\ (y_n = 2) = Pr\ (\mu_1 < z_n \le \mu_2) \\
&= Pr\ (\varepsilon_n \le \mu_2 - \beta X_n) - Pr\ (\varepsilon_n \le \mu_1 - \beta X_n) \\
&= \Lambda(\mu_2 - \beta X_n) - \Lambda(\mu_1 - \beta X_n)
\end{aligned}
\tag{3.19}
$$

$$
\begin{aligned}
P_n(i) &= Pr\ (y_n = i) = Pr\ (\mu_{i-1} < z_n \le \mu_i) \\
&= Pr\ (\varepsilon_n \le \mu_i - \beta X_n) - Pr\ (\varepsilon_n \le \mu_{i-1} - \beta X_n) \\
&= \Lambda(\mu_i - \beta X_n) - \Lambda(\mu_{i-1} - \beta X_n), i = 3 \\
P_n(I) &= Pr\ (y_n = I) = Pr\ (\mu_{I-1} < z_n) = Pr\ (\mu_{I-1} < \beta X_n + \varepsilon_n) \\
&= Pr\left(\mu_{I-1} - \beta X_n < \varepsilon_n\right) = 1 - \Lambda(\mu_{I-1} - \beta X_n), I = 4
\end{aligned}
$$

where, $\Lambda(.)$ = Standard logistic cumulative distribution function of the disturbance term, ε_n.

The probabilities in Eq. 3.19 will be positive if the thresholds parameters follow the constraints $\mu_1 < \mu_2 < \mu_3$ (O'Donnell and Connor, 1996).

Figure 3.1 illustrates the agreement between unobserved, continuous variable, z_n, and observed discrete variable, y_n.

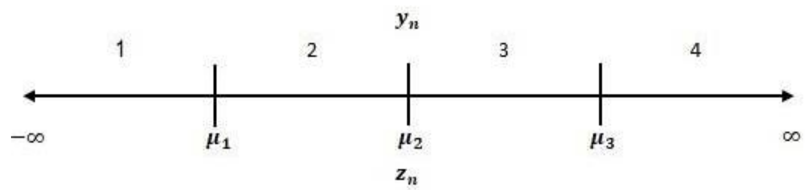


Fig. 3.1: Relationship between unobserved and observed injury variables.

The parameters of ordered logit paradigms are estimated by the method of maximum likelihood (ML). For a sample of N observations, the log-likelihood function can be written as:

$$LL = \sum_{n=1}^{N} \left(\sum_{i=1}^{I} \delta_{ni} LN[\Lambda(\mu_i - \beta X_n) - \Lambda(\mu_{i-1} - \beta X_n)]\right) \tag{3.20}$$

where, all terms are predefined.

3.4.2.3 Model Identification

Mean and variance of the unobserved variable, z_n cannot estimated as the variable is latent in nature. Therefore, the variance is identified by assuming Var $\varepsilon = \pi^2/3$ in ordered logit model (Long, 1997). However, the mean of z_n still remains unidentified.

The non-identification of the model can be shown revising Eq. (12) for a single independent variable as:

$$z_n = a + \beta X_n + \varepsilon_n \tag{3.21}$$

where, $a =$ Intercept, and all terms are previously defined.

The assumed cut-off points (thresholds) for this model, μ_i (where $i = 1, 2, \dots, -1$), and a are considered to be 'true parameters' as they are used to generate the observed data. Defining an alternative set of parameters such that:

$$a^* = a - \varphi \tag{3.22}$$

and

$$\mu_i{}^* = \mu_i - \varphi \tag{3.23}$$

where, $\varphi =$ Arbitrary constant.

The probability that $y = i$ can be written as:

$$\begin{aligned} P_n(i) &= \Lambda(\mu_i - a - \beta X_n) - \Lambda(\mu_{i-1} - a - \beta X_n) \\ &= \Lambda(\mu_i^* - a^* - \beta X_n) - \Lambda(\mu_{i-1}^* - a^* - \beta X_n) \end{aligned} \tag{3.24}$$

Here, both sets of parameters are generating same value of probability for a given observed outcome leaving no way to choose between the parameter sets using the observed data. So, it can be surmised that the model is unidentified.

Dual assumptions regarding parameters, a and μ_i can engender an identifiable model, which eventually lead to an arbitrary choice of $\mu_i = 0$, and $a \neq 0$ in our case. Eq. 3.19, then can be synopsized as:

$$\begin{gathered} P_n(1) = \Pr(y_n = 1) = \Lambda(-\beta X_n) \\ P_n(2) = \Pr(y_n = 2) = \Lambda(\mu_2 - \beta X_n) - \Lambda(-\beta X_n) \\ P_n(3) = \Pr(y_n = 3) = \Lambda(\mu_3 - \beta X_n) - \Lambda(\mu_2 - \beta X_n) \\ P_n(4) = \Pr(y_n = 4) = 1 - \Lambda(\mu_3 - \beta X_n) \end{gathered} \tag{3.25}$$

The following figure shows the probability distribution function (pdf) of a logistically distributed ordered probability model with $\mu_1 = 0$.

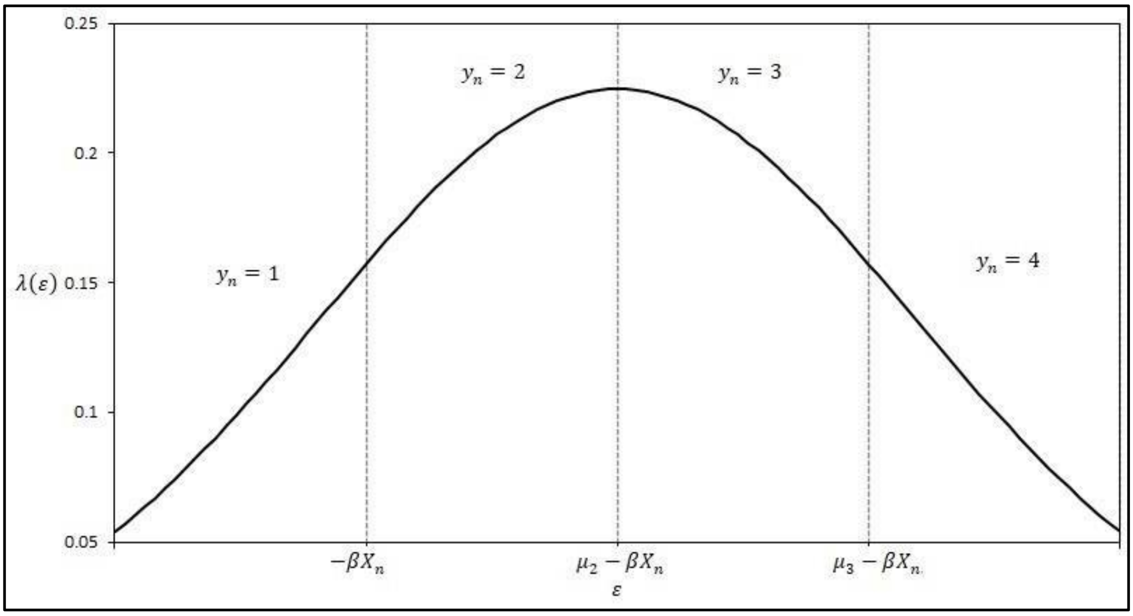


Fig. 3.2: Illustrates an ordered logit model with $\mu_1 = 0$.

3.4.2.4 Elasticity Determination

The effect of the exogenous variables on the response variables often create issues in deciphering the parameter estimates. A positive sense of β in Fig. 3.2 signifies that an increase in X_n will generate the increase (or, decrease) of the probabilities of the highest (or, lowest) ordered injury severity outcomes. However, it is baffling to interpret the trend of the probabilities of the transitional severity levels based on the sense (i.e., positive, or negative) of β. Hence, the calculation of elasticities to evaluate the marginal effects for each level is essential (Washington et al., 2011; Garrido et al., 2014).

For continuous variables, the elasticities measuring the effects on probabilities of different outcome levels can be expressed as:

$$\frac{\partial P(y_n=i)}{\partial X} = [\Lambda(\mu_i - \beta X_n) - \Lambda(\mu_{i-1} - \beta X_n)]\beta \tag{3.26}$$

where, all terms are previously defined.

In case of categorical explanatory variables, Eq. 3.26 is not valid resulting in adoption of a different approach. The effect of the change of an indicator variable from 0 to 1, holding all other variables values at their means, on the probabilities of response variable can be accounted as (Garrido et al., 2014):

$$X_n = P(y_n = i \mid X_n = 1) - P(y_n = i \mid X_n = 0) \tag{3.27}$$

where, all terms are predefined.

3.4.2.5 Model Limitations

Flexibility: Ordered logit model is not suitable for crash severity analysis because it restricts the effects of variables across outcomes (Khorashadi et al., 2005; Washington et al., 2011). The air bag incident provided by Washington et al. (2011) is an important explanation to this limitation. The authors considered three scenario of severity levels namely, PDO, injury, and fatality. The air bag deployment indicator variable in ordered response model would either increase fatality and decrease PDO, or decrease fatality and increase PDO. However, the deployment of air bag itself would increase the probability of injury, which cannot be explained using this kind of model structure. Eluru, Bhat and Hensher (2008) also pointed that ordered specifications hold fixed threshold values across crashes, which in turn lead to incompatible injury risk propensity, and inconsistent effects of variables on injury severity levels.

3.4.3 Ordered Probit (OP) Model

3.4.3.1 Model Assumption

a) Follows parallel lines assumption like the OL model.

b) Disturbance term is assumed to be normally distributed across observations.

c) Assumption is made considering homoskedastic nature of disturbance term (i.e., the variance of disturbance term cannot vary across observations).

d) The disturbance terms for different observations are assumed to be uncorrelated.

3.4.3.2 Mathematical Interpretation

Ordered probit model is typically defined in a latent (i.e., unobserved) variable structure like the OL model. The general specification of each single equation model is,

$$z_n = \beta X_n + \varepsilon_n \tag{3.28}$$

where, z_n = Latent continuous variable measuring the risk of injury faced by observation n in a crash.

$X_n = p \times 1$ vector of non-stochastic (i.e., non-random) explanatory variables measuring the attributes of observation n.

$\beta = p \times 1$ vector of parameters to be estimated.

ε_n = Random disturbance term.

The error term is assumed to be normally distributed across observations with mean $= 0$, and variance $= 1$, which eventually results in an ordered probit model (Washington et al., 2011). The probability density function (pdf) is,

$$\phi(\varepsilon) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\varepsilon^2}{2}\right) \tag{3.29}$$

The cumulative density function (cdf) is,

$$\Phi(\varepsilon) = \int_{-\infty}^{\varepsilon} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt \tag{3.30}$$

The unknown parameter β is to be estimated; however, standard regression technique cannot be applied to Eq. 3.28, as dependent variable, z_n is unobserved (O'Donnell and Connor, 1996). Instead, the observed and coded discrete injury severity variable, y_n contained in the data is used, and a relation is drawn with the latent variable, z_n as follows:

$$y_n = \begin{cases} 1, & -\infty \leq z_n \leq \mu_1 \quad \text{(Motor Collison)} \\ 2, & \mu_1 < z_n \leq \mu_2 \quad \text{(Simple Injury Accident)} \\ 3, & \mu_2 < z_n \leq \mu_3 \quad \text{(Grievous Accident)} \\ 4, & \mu_3 < z_n \leq \infty \quad \text{(Fatal Accident)} \end{cases} \tag{3.31}$$

where, the threshold values μ_1, μ_2 and μ_3 are unknown estimable parameters. This implies that the probability of injury severity i sustained by observation n is the same as the probability that an unobserved variable z_n measuring injury risk, takes a value between two thresholds. The cumulative probability for a given crash n with injury severity levels i can be expressed as follows:

$$P(y_n < i) = \frac{\exp[\mu_i - \beta X_n]}{1 + [\mu_i - \beta X_n]} \tag{3.32}$$

where, y_n = Recorded crash injury severity for crash n.

i = Crash injury severity levels: 1, 2..., $I-1$.

μ_i = Cut-off point for level i.

$X_n = p \times 1$ vector containing the values of all p predictor variables for crash n.

$\beta = p \times 1$ vector of estimable parameters associated with X_n.

The probabilities associated with the coded responses of an ordered probit model can be further shown as,

$$
\begin{aligned}
P_n(1) &= Pr\ (y_n = 1) = Pr\ (z_n \leq \mu_1) = Pr\ (\beta X_n + \varepsilon_n \leq \mu_1) \\
&= Pr\ (\varepsilon_n \leq \mu_1 - \beta X_n) = \Phi(\mu_1 - \beta X_n) \\
P_n(2) &= Pr\ (y_n = 2) = Pr\ (\mu_1 < z_n \leq \mu_2) \\
&= Pr\ (\varepsilon_n \leq \mu_2 - \beta X_n) - Pr\ (\varepsilon_n \leq \mu_1 - \beta X_n) \\
&= \Phi(\mu_2 - \beta X_n) - \Phi(\mu_1 - \beta X_n) \\
P_n(i) &= Pr\ (y_n = i) = Pr\ (\mu_{i-1} < z_n \leq \mu_i) \\
&= Pr\ (\varepsilon_n \leq \mu_i - \beta X_n) - Pr\ (\varepsilon_n \leq \mu_{i-1} - \beta X_n) \\
&= \Phi(\mu_i - \beta X_n) - \Phi(\mu_{i-1} - \beta X_n), i = 3 \\
P_n(I) &= Pr\ (y_n = l) = Pr\ (\mu_{l-1} < z_n) = Pr\ (\mu_{l-1} < \beta X_n + \varepsilon_n) \\
&= Pr\ (\mu_{l-1} - \beta X_n < \varepsilon_n) = 1 - \Phi(\mu_{l-1} - \beta X_n), I = 4
\end{aligned}
\tag{3.33}
$$

where, $\Phi\ (.)$ = Standard normal cumulative distribution function of the disturbance term, ε_n.

The probabilities in Eq. 3.31 will be positive if the thresholds parameters follow the constraints $\mu_1 < \mu_2 < \mu_3$ (O'Donnell and Connor, 1996).

Figure 3.3 illustrates the agreement between unobserved, continuous variable, z_n, and observed discrete variable, y_n.

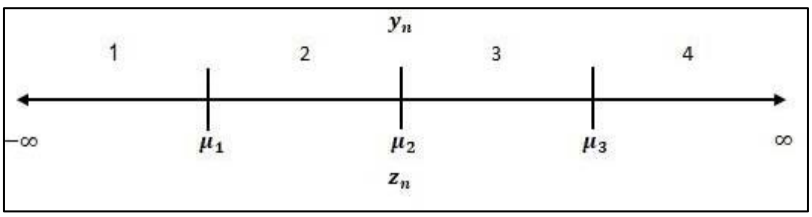


Fig. 3.3: Relationship between unobserved and observed injury variables.

The parameters of ordered probit paradigms are estimated by the method of maximum likelihood (ML). For a sample of N observations, the log-likelihood function can be written as:

$$LL = \sum_{n=1}^{N} \left(\sum_{i=1}^{I} \delta_{ni} LN[\Phi(\mu_i - \beta X_n) - \Phi(\mu_{i-1} - \beta X_n)]\right) \quad (3.34)$$

where, all terms are predefined.

3.4.3.3 Model Identification

Mean and variance of the unobserved variable, z_n cannot estimated as the variable is latent in nature. Therefore, the variance is identified by assuming $\mathrm{Var}\ \varepsilon = 1$ in ordered probit model (Long, 1997). However, the mean of z_n still remains unidentified.

The non-identification of the model can be shown revising Eq. (12) for a single independent variable as:

$$z_n = a + \beta X_n + \varepsilon_n \quad (3.35)$$

where, a = intercept, and all terms are previously defined.

The assumed cut-off points (thresholds) for this model, μ_i (where $= 1, 2, ..., I - 1$), and a are considered to be 'true parameters' as they are used to generate the observed data. Defining an alternative set of parameters such that:

$$a^* = a - \Phi \quad (3.36)$$

and

$$\mu^* = \mu_i - \Phi \quad (3.37)$$

where, φ = arbitrary constant.

The probability that , $y = i$ can be written as:

$$\begin{aligned} P_n(i) &= \Phi(\mu_i - a - \beta X_n) - \Phi(\mu_{i-1} - a - \beta X_n) \\ &= \Phi(\mu_i^* - a^* - \beta X_n) - \Phi(\mu_{i-1}^* - a^* - \beta X_n) \end{aligned} \quad (3.38)$$

Here, both sets of parameters are generating same value of probability for a given observed outcome leaving no way to choose between the parameter sets using the observed data. So, it can be deduced that the model is unidentified.

Dual assumptions regarding parameters, a and μ_1 can engender an identifiable model, which eventually lead to an arbitrary choice of $\mu_1 = 0$, and $a \neq 0$ in this thesis. Eq. 3.33, then can be synopsized as:

$$\begin{gathered} P_n(1) = Pr\,(y_n = 1) = \Phi(-\beta X_n) \\ P_n(2) = Pr\,(y_n = 2) = \Phi(\mu_2 - \beta X_n) - \Phi(-\beta X_n) \\ P_n(3) = Pr\,(y_n = 3) = \Phi(\mu_3 - \beta X_n) - \Phi(\mu_2 - \beta X_n) \\ P_n(4) = Pr\,(y_n = 4) = 1 - \Phi(\mu_3 - \beta X_n) \end{gathered} \qquad (3.39)$$

The following figure shows the probability distribution function (pdf) of a normally distributed ordered probability model with $\mu_1 = 0$.

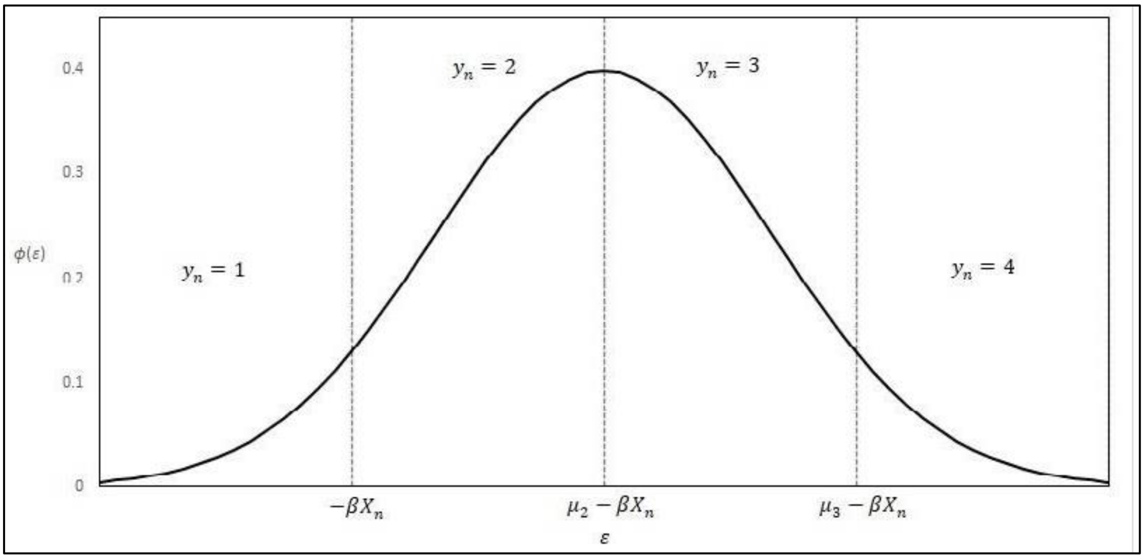


Fig. 3.4: Illustrates an ordered probit model with $\boldsymbol{\mu_1 = 0}$.

3.4.3.4 Elasticity Determination

See section 3.4.2.4.

3.4.3.5 Model Limitations

See section 3.4.2.5.

3.4.4 Partial Proportional Odds (PPO) Model

3.4.4.1 Assumption

a) Partially relaxes the parallel odds assumption for some variables.

3.4.4.2 Mathematical Interpretation

The general cumulative probability function of injury severity level i for a given crash n can be written as (Mooradian et al., 2013)s:

$$P(y_n \leq i) = F(\mu_i - \beta X_n - \gamma_i T_n) = \frac{\exp[\mu_i - \beta X_n - \gamma_i T_n]}{1 + \exp\,[\mu_i - \beta X_n - \gamma_i T_n]} \tag{3.40}$$

where, y_n = Recorded crash injury severity for crash n.

i = Crash injury severity levels: 1, 2…, $I - 1$.

$F(.)$ = Standard cumulative distribution function.

μ_i = Cut-off point for level i.

$X_n = p \times 1$ vector containing the values of all p predictor variables for crash n.

$\beta = p \times 1$ vector of estimable parameters associated with X_n.

$T_n = q \times 1$ vector ($q \leq p$), containing the values of all predictor variables on the subset of p for crash n, where proportional odds assumption is rejected.

$y_i = q \times 1$ vector of estimable parameters associated with T_n, such that $y_i T_n$ corresponds only to the i th level of injury severity for observation n, and $y_i = 0$.

A key problem of parallel-lines model like, proportional odds (PO) model is that its assumptions are often violated; it is common for one or more β's to vary across the values of i; i.e., parallel-lines model is overly restrictive (Williams, 2006). The only difference the PPO model has with the PO model is the way PPO partially relaxes the parallel odds assumption for a particular set of variables, which generally is a subset of the set of total predictor features available in the data. Eq. 3.18 implies that the value of the estimable parameter β for each explanatory variable is restricted to be identical across all the severity levels, i. In other words, the parallel odds assumption in PO model signifies that, $\beta_1 = \beta_2 = \cdots = \beta_{i-1} = \beta$, which is relatively true for PPO model. Eq. 3.40 shows the inclusion of an additional parameter y_i which vary across i for an observation n. The PPO model only restricts the parameters which follows the parallel lines assumption.

Let's consider a particular variable X_{ns} where $s \in q$ i.e., the variable violates proportional odds assumption. The available parameters associated with X_{ns} will be the coefficient β_s (same across the values of i), and the coefficient y_s (different across the values of i). Now for a specific level i, the true coefficient of X_{ns} is equal $\beta_s + y_{is1}$ (considering y_{is1} be value of y_{is} for that specific level i).

Eq. 40 can also be deduced into multinomial and order response models. If $q = 0$, then the preceding equation becomes,

$$F(\mu_i - \beta X_n) = \frac{exp[\mu_i - \beta X_n]}{1 + exp\ [\mu_i - \beta X_n]} \tag{3.41}$$

which corresponds to an order response model.

Again, if $q = p$, then Eq. 27 becomes,

$$F(\mu_i - \beta_i X_n) = \frac{\exp[\mu_i - \beta_i X_n]}{1 + \exp\ [\mu_i - \beta_i X_n]} \tag{3.42}$$

which dovetails the cumulative density function of multinomial model.

The probabilities associated with the coded responses of a PPO model can be shown as:

$$\begin{gathered} Pr\ (y_n = 1) = F(\mu_1 - \beta X_n - \gamma_1 T_n) \\ Pr\ (y_n = 2) = F(\mu_2 - \beta X_n - \gamma_2 T_n) - F(\mu_1 - \beta X_n - \gamma_1 T_n) \\ Pr\ (y_n = i) = F(\mu_i - \beta X_n - \gamma_i T_n) - F(\mu_{i-1} - \beta X_n - \gamma_{i-1} T_n), i = 3 \\ Pr\ (y_n = I) = 1 - F(\mu_{I-1} - \beta X_n - \gamma_{I-1} T_n), I = 4 \end{gathered} \tag{3.43}$$

where, all terms are predefined.

For the ease of interpretation, a slightly altered version of Eq. 40 is as follows:

$$p(y_n \geq i) = G(\mu_i + aX_n + b_i T_n \tag{3.44}$$

where, $G(.) = 1 - F(.)$.

$a = -\beta$.

$c_i = y_i$.

In this method, the Motor Collision result level, which is the lowest level of outcome, will serve as the reference level. Consequently, a positive value will imply a larger probability of a higher severity level (i.e., fatal), while a negative sense will indicate a decreased probability (Mooradian et al., 2013).

3.5 Model Selection

The intrinsic trait of an ideal model selection approach is to stabilize goodness of fit with simplicity. This section structures about the rationale of criteria for statistical model selection from a set of candidate models.

3.5.1 Fit Adequacy

The degree to which a paradigm successfully fits the observed data is referred to as its "goodness of fit," which also captures the difference between expected and observed values. The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and McFadden's Pseudo R-Squared are utilized criteria in this context to evaluate the fit adequacy of candidate models. The mistake percentages for the two paradigms utilized for the severity analysis are also evaluated using MAPE.

3.5.1.1 Akaike Information Criterion (AIC)

The AIC acts as an estimator of the relative standard of statistical paragons for a given dataset, motivating the selection of appropriate paragons. More precisely, AIC is single number score identifying the suitable model among a number of models that better fits the given set of data. AIC value of a model is represented as follows:

$$AIC = -2\ln(L) + 2k \tag{3.45}$$

where, $L =$ Maximum value of likelihood function for the model.

$k =$ Number of estimated parameters in the model.

AIC primarily uses maximum likelihood estimation (log-likelihood) of the model to assess fitness sufficiency. For models with high log-likelihood, the AIC value is low, which implies that a lower AIC value is preferable.

The penalty term $2k$ in Eq. 3.45, which represents overfitting of the model's parameters, increases model complexity while maintaining appropriate goodness of fit. AIC doesn't give any warning if all candidate models fit poorly because it measures the model's relativity.

AIC calculates the relative loss of this information. Any model reflecting the process that produced the data will lose some information along the way. It is decided to choose the model that minimizes the loss, however this decision is uncertain.

3.5.1.2 Bayesian Information Criterion (BIC)

The Bayesian Information Criterion (BIC) is a standard for model selection which is closely related to the Akaike Information Criterion (AIC). The BIC is structured as follows:

$$BIC = -2\ln(L) + \ln(n)k \tag{3.46}$$

where, $L =$ Maximum value of likelihood function for the model.

$k =$ Number of estimated parameters in the model.

$n =$ Number of observations (i.e., sample size).

However, BIC assumes that sample size n is much larger than parameters k in the model. The one with the lowest value of BIC is selected among various paradigms that generated the data like the AIC.

Overfitting with complexity is also an issue in BIC; however, the penalty term in BIC $\ln(n)k$ is larger than $2k$. Another fact is that BIC can only be used as an estimator if the response values of dependent variable are identical for all models being compared.

3.5.1.3 McFadden's Pseudo ρ-Square

A common weapon of model fit is McFadden's ρ^2 statistic which is almost similar to McFadden's R^2 in regression models in terms of purpose. The statistic is expressed as:

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{3.47}$$

where, $LL(\beta) =$ Model's log likelihood at convergence.

$LL(0) =$ Log likelihood when all parameters are set to 0.

This statistic is also known as likelihood ratio index. The value of ρ^2 ranges from 0 to 1, and the value being close to 1 signifies the parameters are estimated with much conviction (Washington et al., 2011).

3.5.1.4 Mean Absolute Percentage Error (MAPE)

Mean absolute percentage error (MAPE) is a statistical measure that examine the accuracy of the models as a loss function for regression analysis. It looks at the average percentage difference between predicted values and observed values as follows:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{A_i - P_i}{A_i}\right| \times 100\% \tag{3.48}$$

where, $n =$ Total number of observations.

$A_i =$ Observed value.

$P_i =$ Predicted value for observation i.

This standard is easy to interpret as it provides error in terms of percentages.

MAPE being a yardstick of error, high value signifies poor models whereas low value indicates better models. It works best to forecast error if there are no extremes to the data (and no zeros).

3.5.2 Comparison of Predictors

The parameters of the predictor variables that were acquired utilizing the various data-generation techniques are compared. A major worry was the significant coefficients obtained in all of the models used for this investigation. The covariates of the multinomial logit (MNL), partial proportional odds (PPO), and proportional odds (PO) models were contrasted by Mooradian et al. (2013). In terms of parameter values and significance levels, the authors claimed that the PPO model and the MNL model produce findings that are comparable.

3.5.3 Cross-Validation

Cross-validation, commonly referred to as out-of-sample testing, is a well-known method for assessing how well prediction models perform with a given set of data. Models must be tested after being trained using validation datasets (i.e., training datasets), which must both come from the same dataset utilized for this research. In this instance, two non-exhaustive cross-validation techniques are used: k -fold cross-validation and Monte Carlo cross-validation.

3.5.3.1 k-fold Cross-validation (KFCV)

When compared to other exhaustive cross-validation methods, k -fold cross-validation (KFCV), also known as v-fold cross-validation, requires less time for estimation (Beschorner et al., 2014). In this method of cross-validation, the primary sample is divided into k identically sized subsamples; 10-fold cross-validation is used to determine the optimum model for the scenario in Bangladesh. The remaining subsample is utilized as the validation set while the remaining k 1 subsamples are used to execute the procedure. After then, the procedure is repeated k times using a different validation set each time. The desired isolated approximation is then obtained by averaging the findings for k. Though, utilizing the full datasets for model validation has one advantage over Monte Carlo cross-validation.

3.6 Summary

The following figure (Fig. 3.5) outlines the methodological steps undertaken to engineer for the purpose of this thesis.

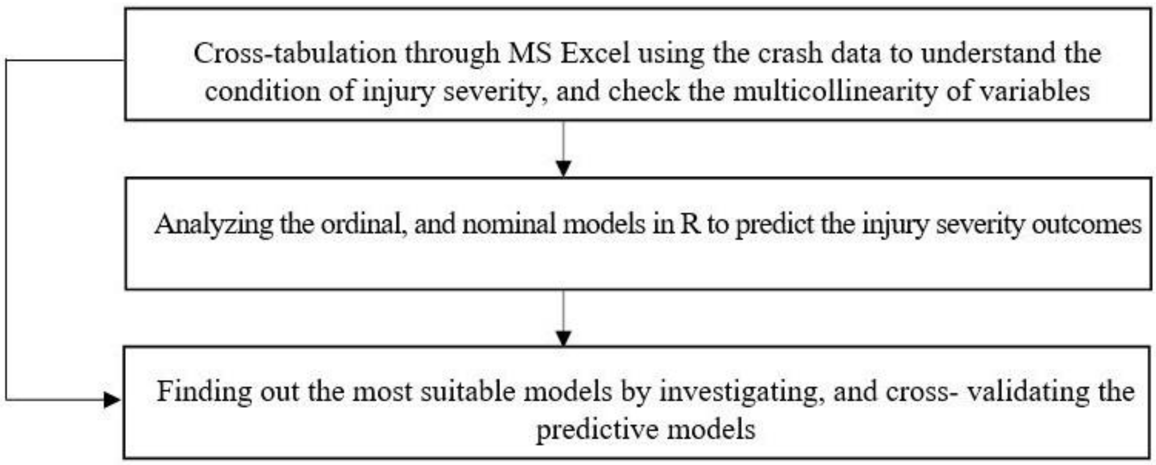


Fig. 3.5: Methodological steps.

CHAPTER 4
PUBLIC BUS SAFETY STATUS IN DHAKA CITY

4.1 Introduction

Official police reports on traffic accidents in Bangladesh provide the impression that the country's standing in terms of traffic safety is improving, but the reality is far different. Police statistics in Bangladesh indicated 2,376 road fatalities in 2016, however a WHO study from 2018 indicates that the true toll was higher than 24,954. The issue is also made worse by the collection of accident data including non-fatal injuries. A summary of Bangladesh's traffic accident database system is provided in this chapter, which has a significant bearing on the thesis's conclusion. Along with the requisite cross-tabulation, this chapter also includes a graphic representation of data on crashes involving public buses.

4.2 Traffic Accident Database System

Police in Bangladesh are in charge of collecting and preserving data on road accidents because they are the most extensively spread institution and have the ability to reach out to the most remote regions of the country. There was no standard format for gathering accident data before to 1996. At the time, information was acquired by local police stations called thanas. Districts and metropolitan police agencies received monthly aggregate reports of the data. Finally, information was compiled for official road accident statistics at the police headquarters (HQ). There was very little value for the statistics, and neither engineering nor research could be done with them.

In June 1995, the Bangladesh Police built a new ARF in cooperation with the Institutional Development Component (IDC), which was tested in the northern division of the Dhaka Metropolitan Police (DMP) area. The Department for International Development (DFID) of the British government provided funding for the IDC of the Second Road Rehabilitation and Maintenance Project (RRMP2). By the end of 1996, all of the DMP's police stations were fully wired onto the network. The new strategy has considerably enhanced the nation's accident information system. The Microcomputer Accident Analysis Package (MAAP) was used to computerize the entire system, which was built by the Transport Research Laboratory (TRL) of the United Kingdom (UK) specifically for storing and analyzing road accident data. Since 1997, this reporting system has been in operation all over the nation, and in September 1999, it was made a requirement for police personnel [Regulation 254(b)].

Table 4-1: Regional ADUs and their Jurisdictions

Location of ADUs	Zonal Jurisdiction
DMP	Dhaka Metropolitan Area
Dhaka Range	Dhaka Division (Except DMP Area)
CMP	Chattogram Metropolitan Area
Chattogram Range	Chattogram Division (Except CMP Area)
RMP	Rajshahi Metropolitan Area
Rajshahi Range	Rajshahi Division (Except RMP Area)
KMP	Khulna Metropolitan Area
Khulna Range	Khulna Division (Except KMP Area)
SMP	Sylhet Metropolitan Area
Sylhet Range	Sylhet Division (Except SMP Area)
BMP	Barisal Metropolitan Area
Barisal Range	Barisal Division (Except BMP Area)
RPMP	Rangpur Metropolitan Area
Rangpur Range	Rangpur Division (Except RPMP Area)
GMP	Gazipur Metropolitan Area
MMP	Yet to be functional

For every kind of collision, a police sub-inspector submits a First Information Report (FIR). This officer must also complete an ARF in the event of a road traffic collision after visiting the site and validating the information. The ARF is subsequently dispatched to the appropriate Accident Data Units (ADU), where the ARF's information and the accident's location are entered into MAAP. Early in 1998, ten regional ADUs were created. These units are responsible for processing and analyzing data from traffic accidents in their respective jurisdictions. Four more ADUs have recently been established, with one more set to open soon (Table 4.1).

An extra ADU was developed at the police headquarters to assemble the national accident database and analyze the data. Data are collected from the regional ADUs in soft (MAAP) format for preservation and to use as a source of intelligence.

The Accident Research Institute (ARI) of the Bangladesh University of Engineering and Technology (BUET) largely uses the MAAP database for research (BUET). The police department and the Road Safety Cell (RSC) of the Bangladesh Road Transport Authority (BRTA) collaborate to transfer this database to ARI. For current road safety studies and investigations, this database serves as the foundation. ARI, on the other hand, collects hard copies (ARFs) and soft copies (MAAP) from ADUs, adds Road User Movement (RUM) codes to enable data analysis, and modifies, validates, and fills in the missing information in MAAP as retrieved from corrected ARFs to enhance the database information. Bengali format of the ARF (currently in use), its English format, and the instruction guide for filling up the ARF is enclosed in Appendix A, Appendix B, and Appendix C sequentially for a clear understanding of the present road accident database system in Bangladesh (Raihan, 2013).

4.3 Public Bus Safety Status in Dhaka

Using straightforward statistical analysis, this part examines the current situation with regard to public bus safety in Dhaka from 2017 to 2020. The process largely comprises creating tables in MS Excel using common cross-tabulation techniques. The link between accident severity and geometric and environmental parameters is the main focus of this study. As a result, the tables are built as a year-by-year distribution of Public bus accident severity for each of the predictors. To better visualize crash frequency, these facts are then turned into graphs that show the size, trends, and characteristics of the accidents. It's important to note that the crash data for public buses is only represented graphically in this chapter. The generated tables are located in Appendix D.

4.3.1 Year-wise accident severities

The public bus crash data that was used in this study had four injury severity outcomes: motor collision (M) (2.1%), simple injury (S) (4.62%), grievous injury (G) (22.6%), and fatal injury (F) (70.68%). The data in Table 4.2 clearly demonstrates the tendency of the data toward fatal accidents and attests to the widespread reporting of fatal accidents in Bangladesh's accident database.

Table 4-2: Year-wise Public Bus Accident Severities

Year	Accident Severity				
	F	G	M	S	Total
2017	110	27	3	9	149
2018	89	31	5	2	127
2019	95	36	1	8	140
2020	58	19	1	4	82
Grand Total	352	113	10	23	498
Percentage	70.68	22.6	2.1	4.62	100

4.3.2 Year-wise accident severities by day of the week, month, year

Figures 4.1, 4.2, and 4.3 provide analyses of accidents for various temporal variables. Regarding the day of the week and the month of the year, no noteworthy accident trend has been found. However, 7:30 am to 8:30 am and 11 am to 5 pm have been the most significant hours of accident occurrences for fatal injury and grievous harm, according to accident analysis regarding the time of occurrence.

4.3.3 Year-wise accidents by junction type

As shown by Figure 4.4, mid-block parts of roadways are more accident-prone than junctions. This is true for all four types of accidents, including those that result in fatalities, serious injuries, motor vehicle collisions, and simple injuries. These incidents have occurred at non-junctional parts in about 58 % of cases. The susceptibility of Tee junctions near not-junction sections is also shown by a surge in all four graphs.

4.3.4 Year-wise accidents by the traffic control system and collision type

Where there is no traffic control system in place, more than 65% of accidents have happened (Figure 4.5). Police-controlled zones have been found to reduce crash severity by statistical modeling, despite having a higher frequency of all crash severities. In terms of fatalities and severe injuries, the collision between a public bus and pedestrians is shown in Figure 4.6 to be the most vulnerable form of collision. Following this category are, in that order, a head-on collision, a sideswipe, and an overturn.

4.3.5 Year-wise accidents by light condition

Daylight have been found to be catalysts for accidents of all kinds (Figures 4.7). General statistics were useful in this case merely to determine the percentages of crashes that occurred under various climatic conditions, but they were unable to provide any insight into the real circumstances. Chapter 5 of this thesis provides the acumens with regard to these characteristics.

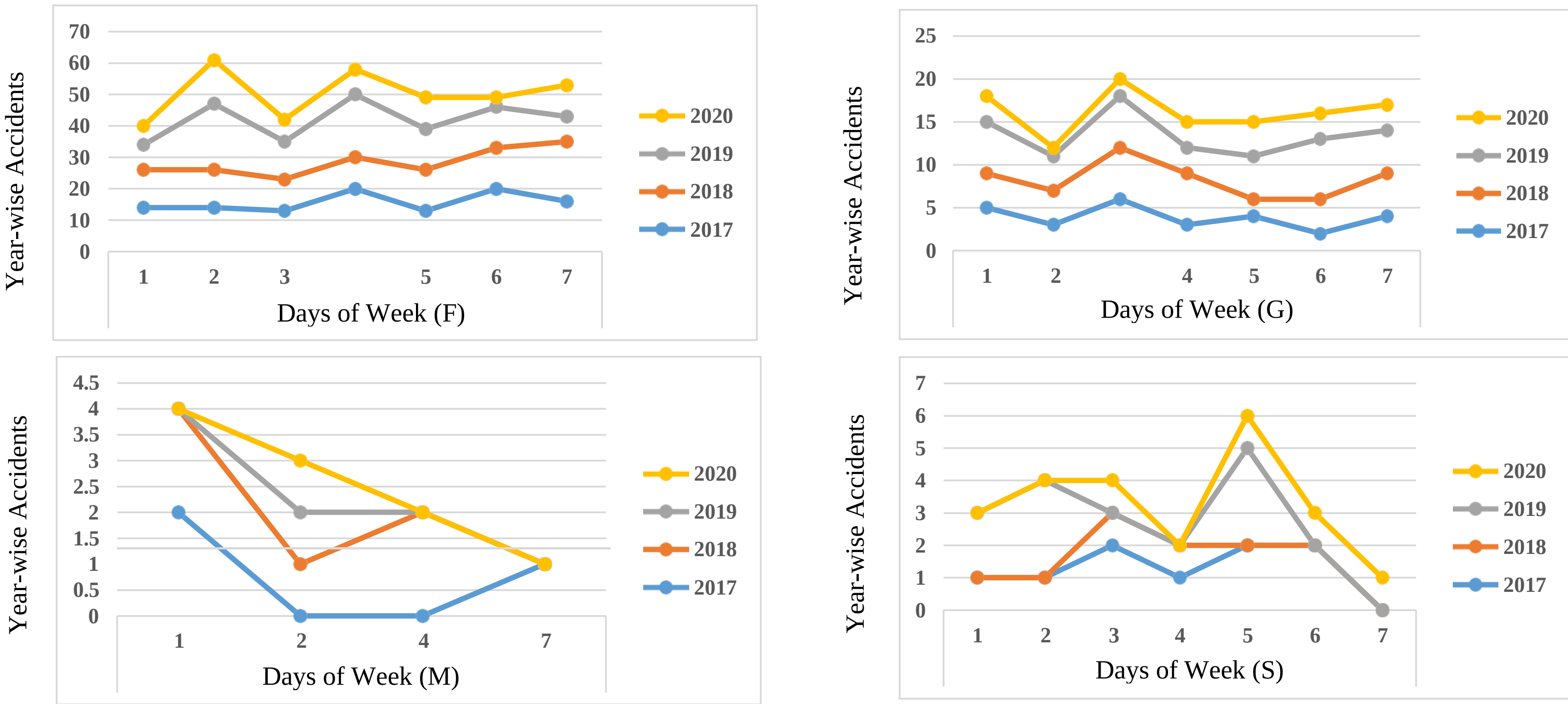
4.3.6 Year-wise accidents by surface condition, type, and quality

According to research, Figures 4.8, 4.9, and 4.10 demonstrate that, in terms of crash frequencies, dry road surface conditions, sealed road surface types, and good road surface quality, respectively.

4.3.7 Year-wise accidents by road class, road feature, and location

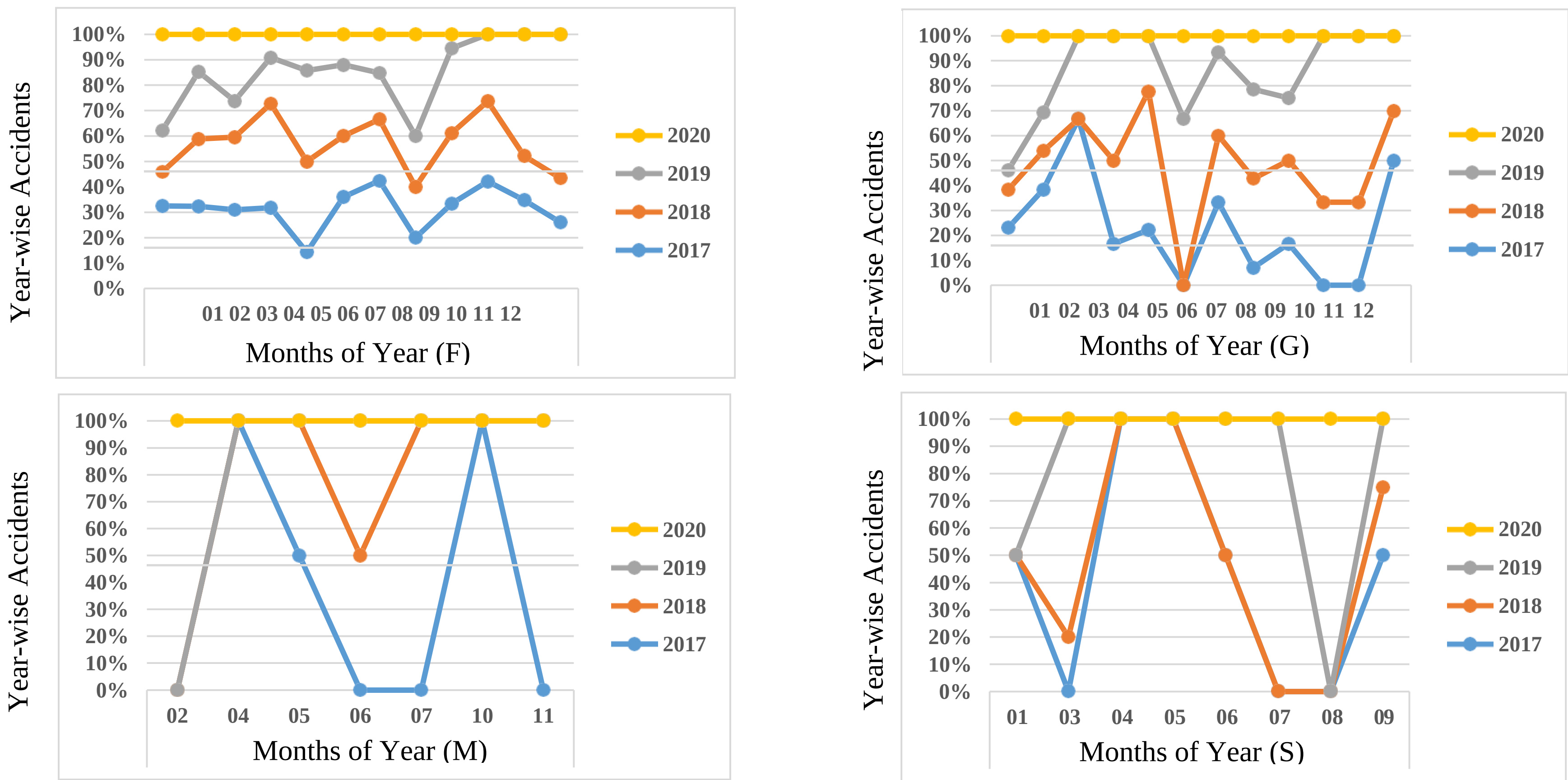
In the case of road class, national highways share the highest crash frequency in terms of fatal, grievous, and simple injury (Figure 4.11). City roads, on the other hand, govern motor collision injury. In addition, these accidents are associated with normal road features (92.7% cases, Figure 4.12) and distributed quite similarly in rural (nearly 55%, decreasing trend) and urban areas (nearly 44%, increasing trend). Detailed statistics are incorporated in Appendix D in Tables 15, 16, and 17.

From the aforementioned statistical analyses, an idea concerning public bus crash data scenario in Dhaka is attained. The discernments gained from these graphical trends were then used in the data processing segment of this study.



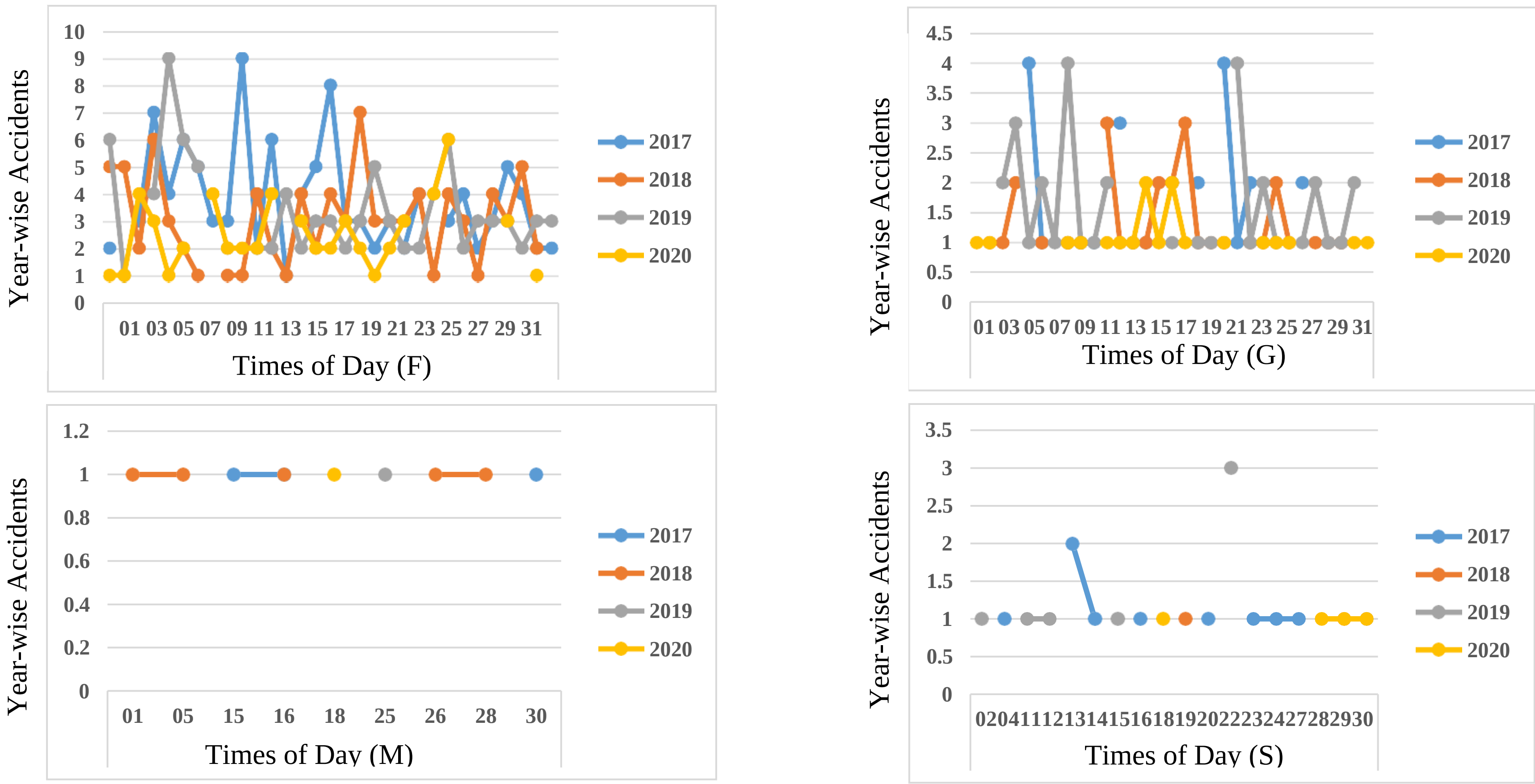
(Note: In the above figure, 1, 2, 3, 4, 5, 6, and 7 stands for Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday, respectively).

Fig. 4.1: Trend of year-wise accidents at different days of week.



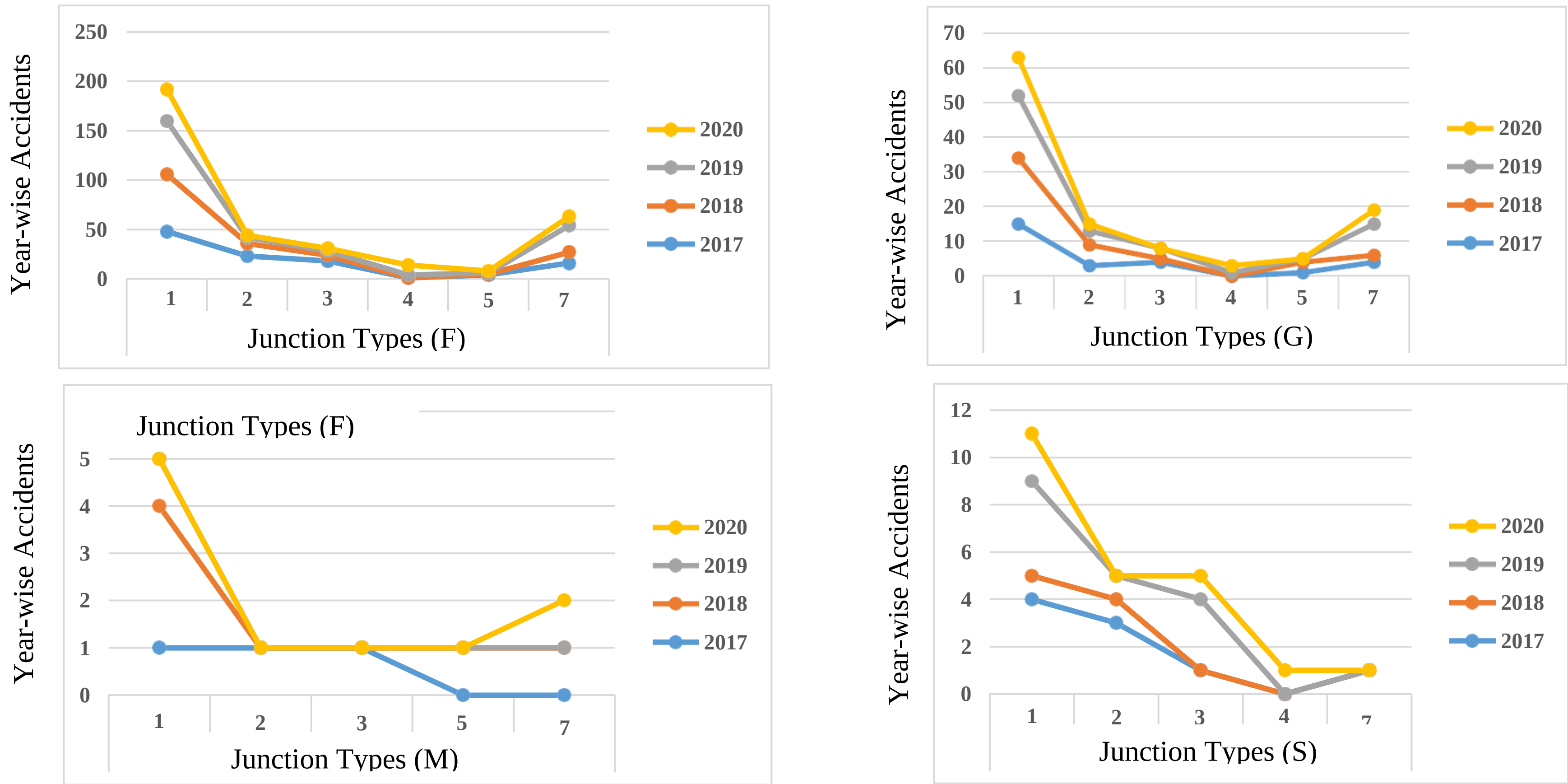
(Note: In the above figure, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, and 12 stands for January, February, March, April, May, June, July, August, September, October, November, December, respectively).

Fig. 4.2: Trend of year-wise accidents at different months of year.



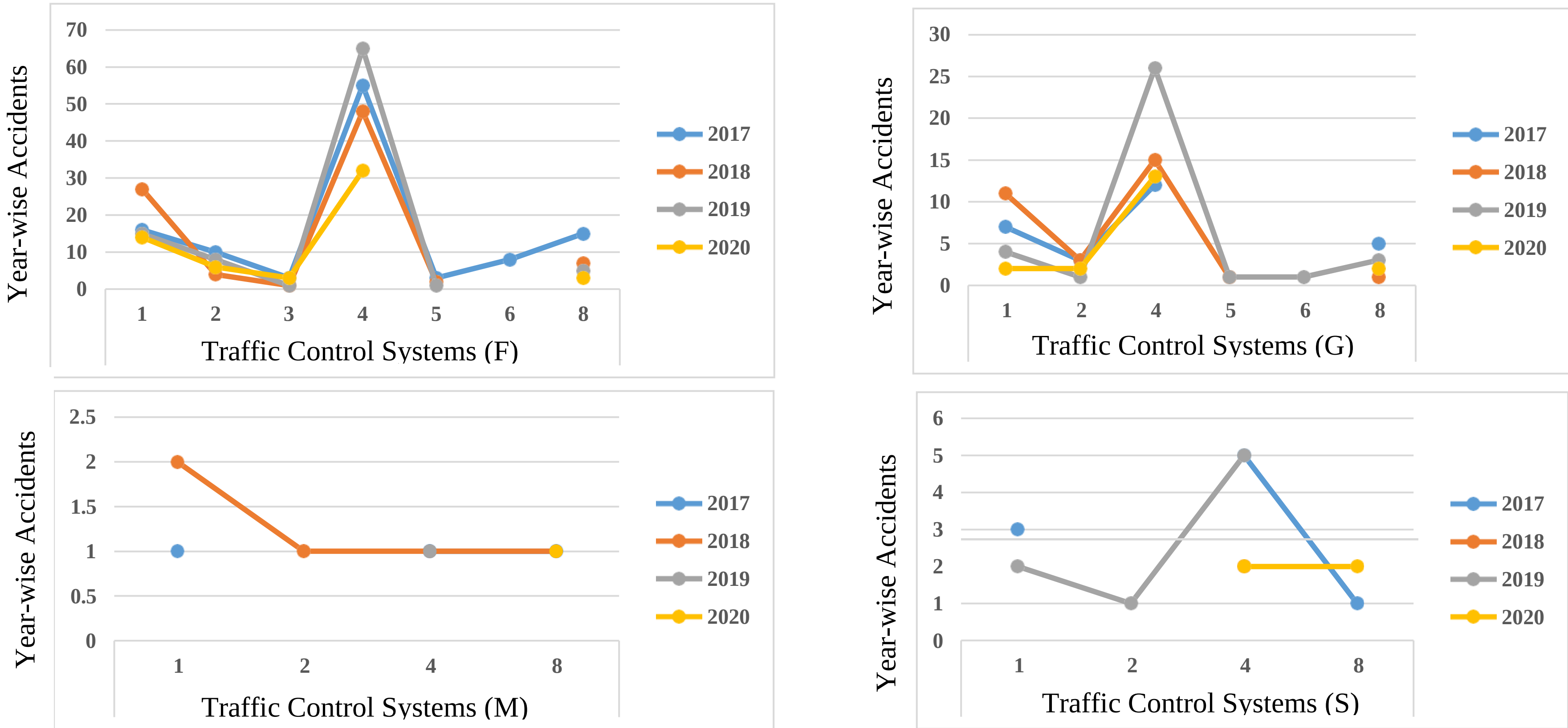
(Note: In the above figure, 25 stands for ?/Blank data field).

Fig. 4.3: Trend of year-wise accidents at different times of day.



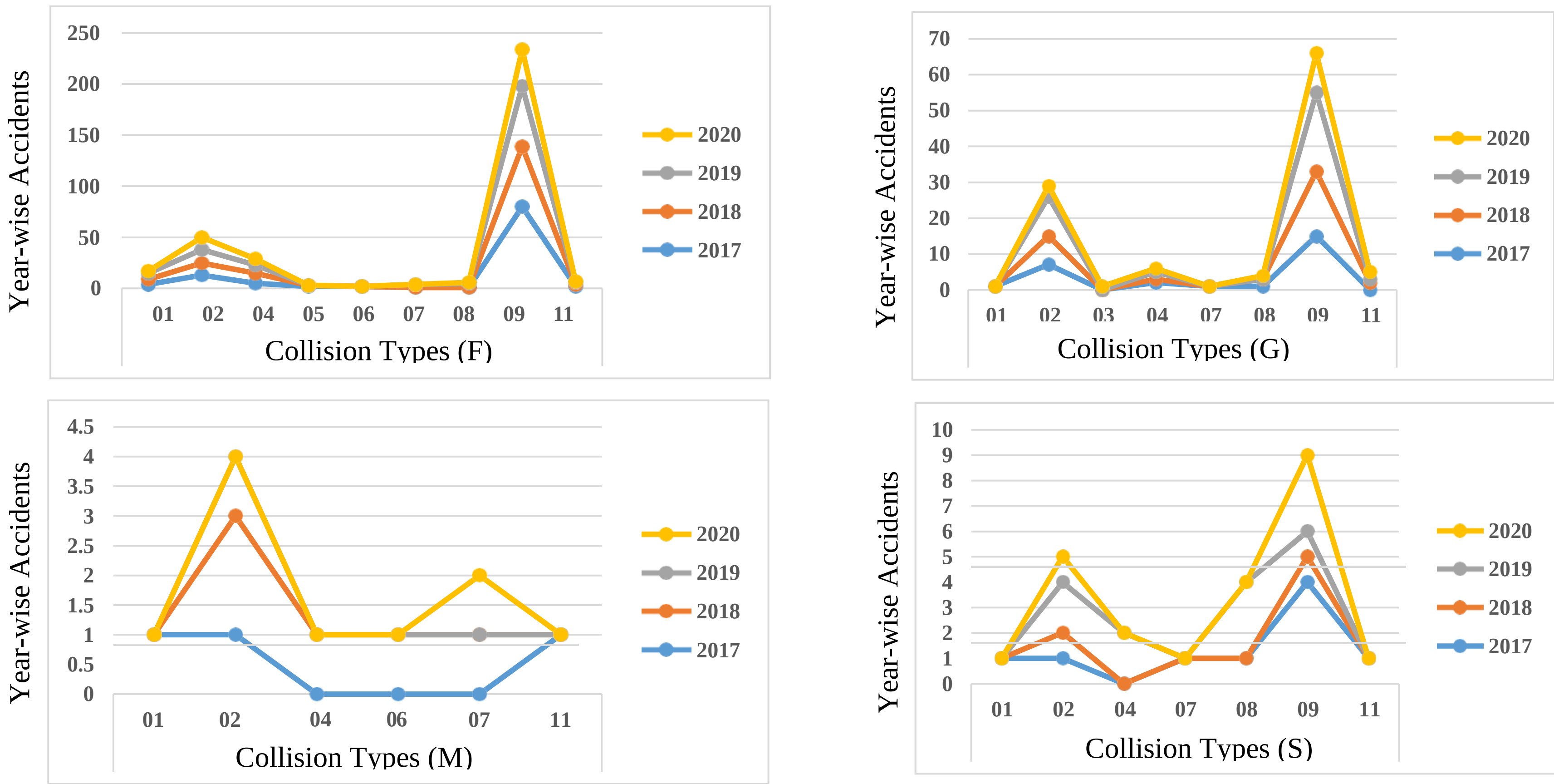
(Note: In the above figure, 1, 2, 3, 4, 5, 6, 7, and 8 stand for Not at a junction, Cross junction, Tee junction, Staggered junction, Roundabout, Railway/Level crossing, Other, and ?/Blank data field, respectively).

Fig. 4.4: Trend of year-wise accidents at different junction types.



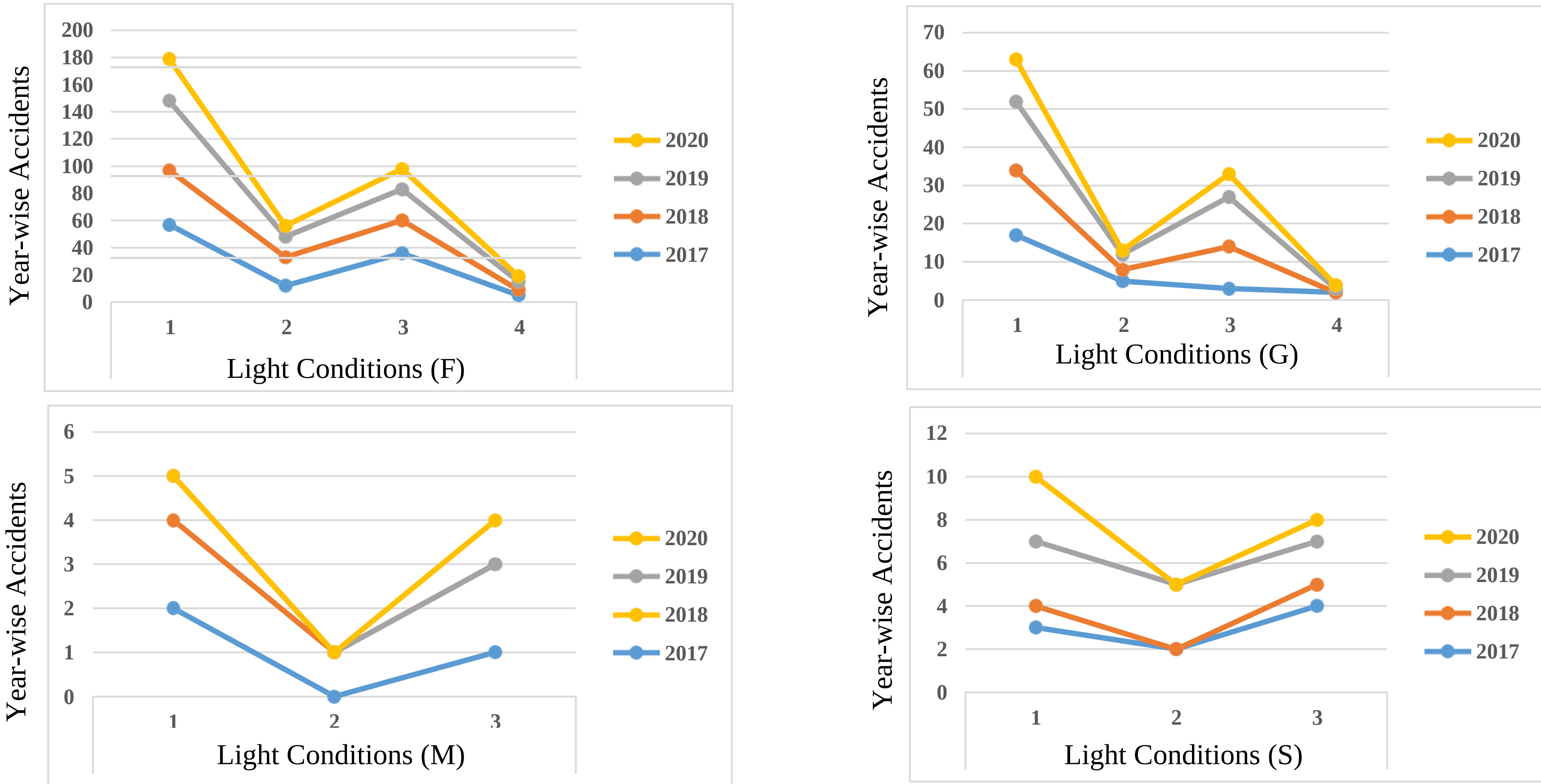
(Note: In the above figure, 1, 2, 3, 4, 5, 6, 7, 8, and 9 stand for No control, Centerline marking, Pedestrian crossing, Police controlled, Traffic lights, Police+Traffic lights, Stop/Give way sign, Other, and ?/Blank, respectively).

Fig. 4.5: Trend of year-wise accidents at different traffic control systems.



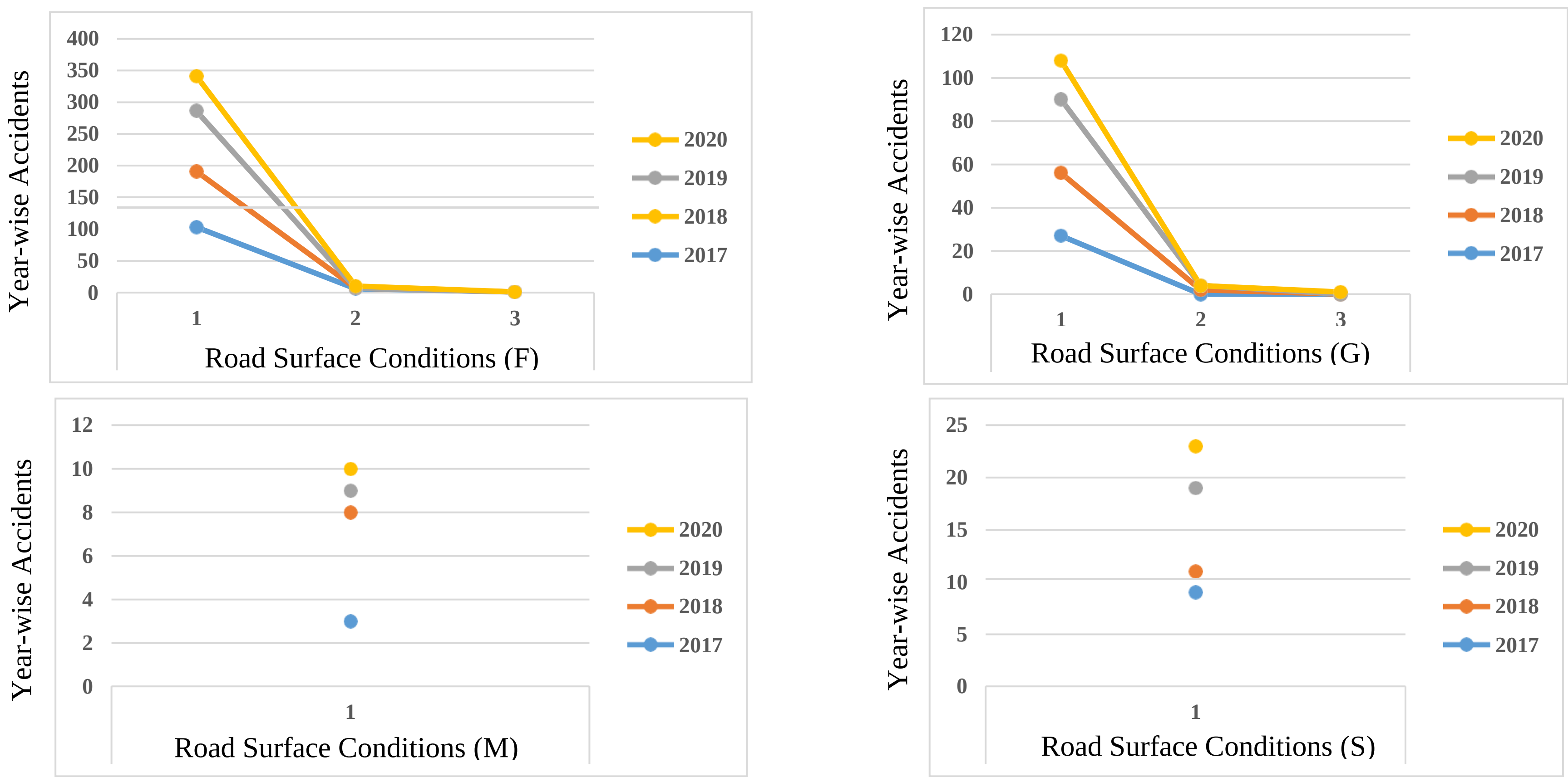
(Note: In the above figure, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, and 12 stand for Head on, Rear end, Right angle, Side swipe, Overturn, Hit object in road, Hit object off road, Hit parked vehicle, Hit pedestrian, Hit animal, Other, and ?/Blank data field, respectively).

Fig. 4.6: Trend of year-wise accidents at different collision types.



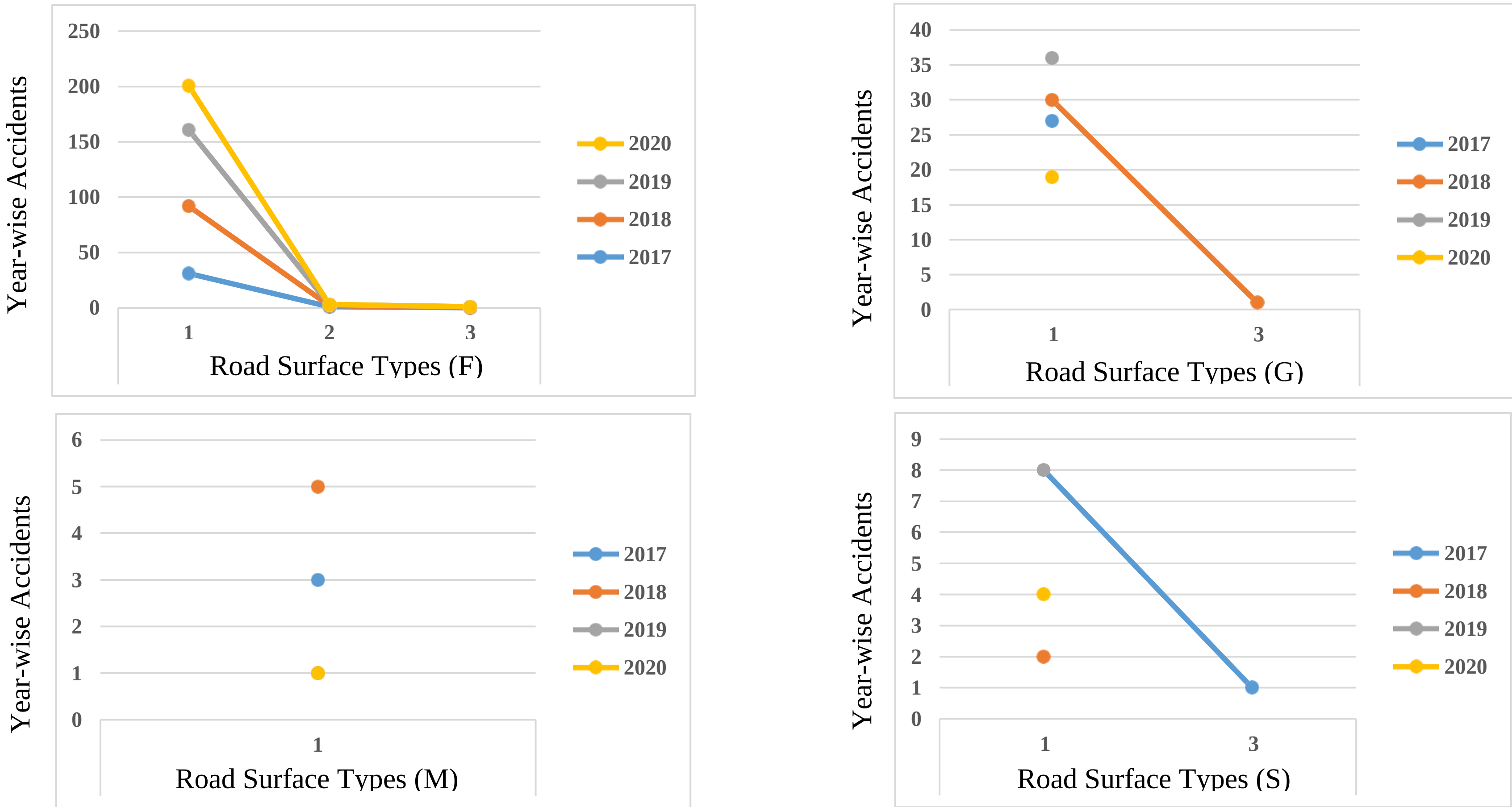
(Note: In the above figure, 1, 2, 3, 4, and 5 stand for Daylight, Dawn/Dusk, Night (lit), Night (unlit), and ?/Blank data field, respectively).

Fig. 4.7: Trend of year-wise accidents at different light conditions.



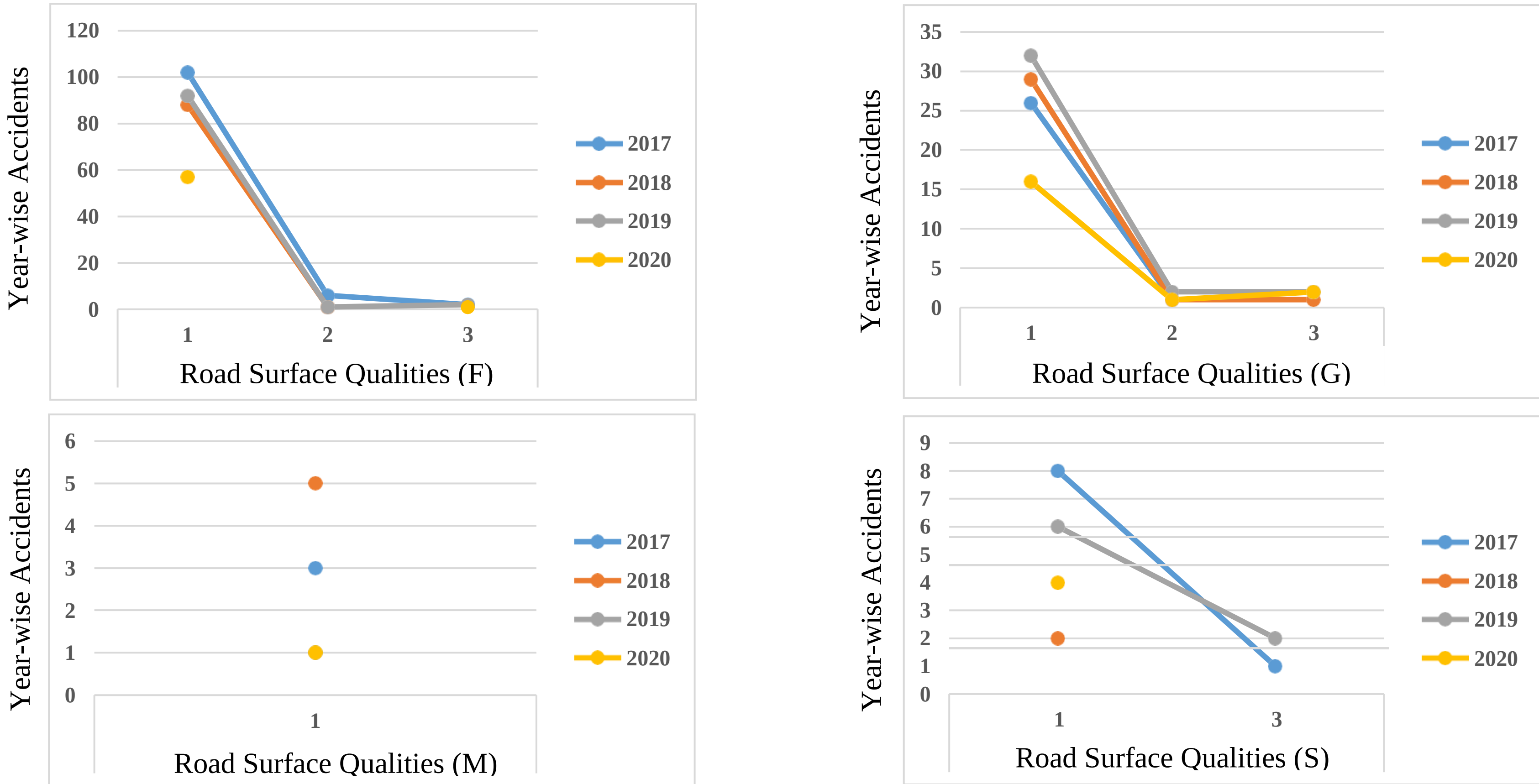
(Note: In the above figure, 1, 2, 3, 4, 5, and 6 stand for Dry, Wet, Muddy, Flooded, Other, and?/Blank data field, respectively).

Fig. 4.8: Trend of year-wise accidents at different road surface conditions.



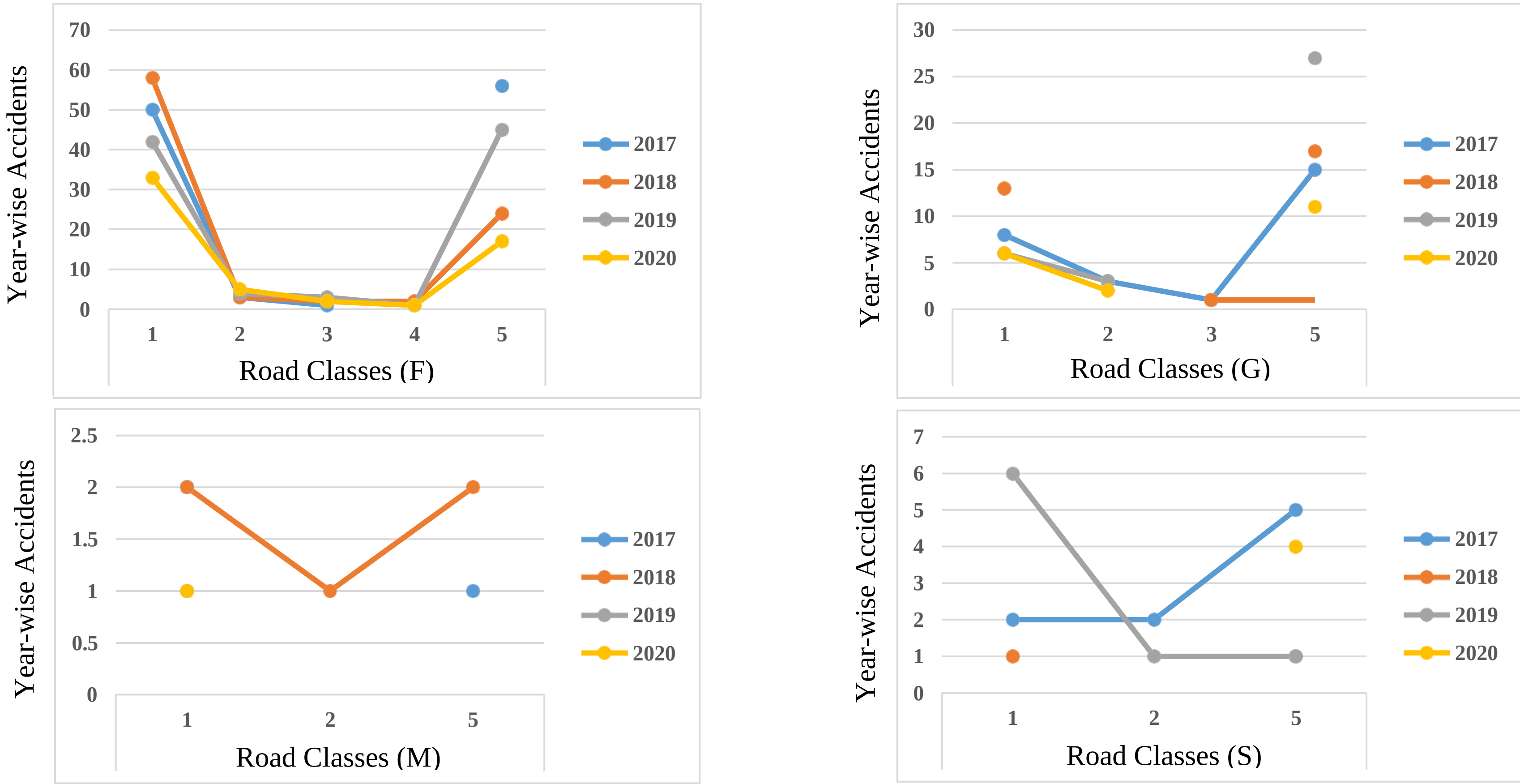
(Note: In the above figure, 1, 2, 3, and 4 stand for Sealed, Brick, Earth, and?/Blank data field, respectively).

Fig. 4.9: Trend of year-wise accidents at different road surface types.



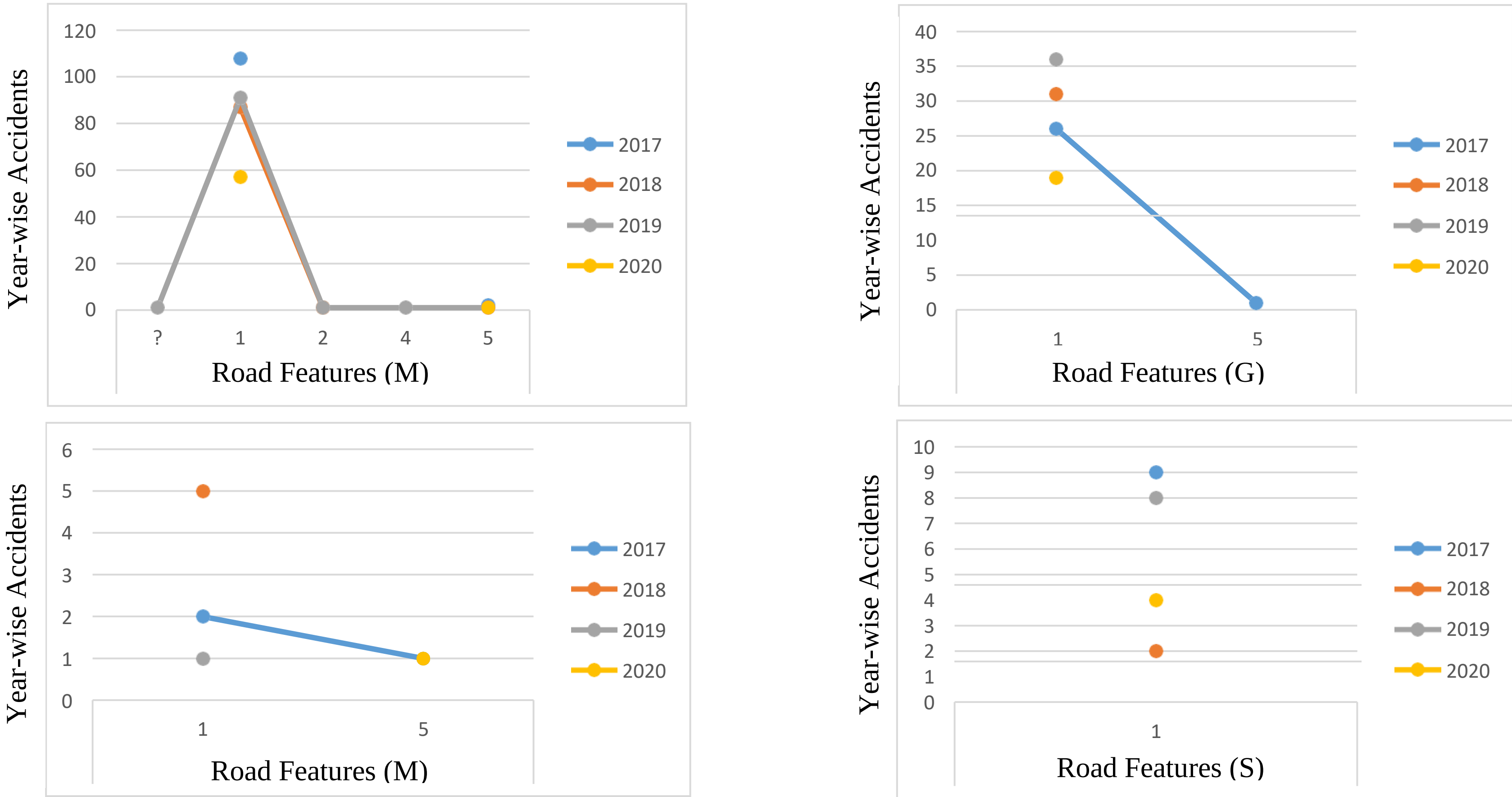
(Note: In the above figure, 1, 2, 3, and 4 stand for Good, Rough, Under repair, and?/Blank data field, respectively).

Fig. 4.10: Trend of year-wise accidents at different road surface qualities.



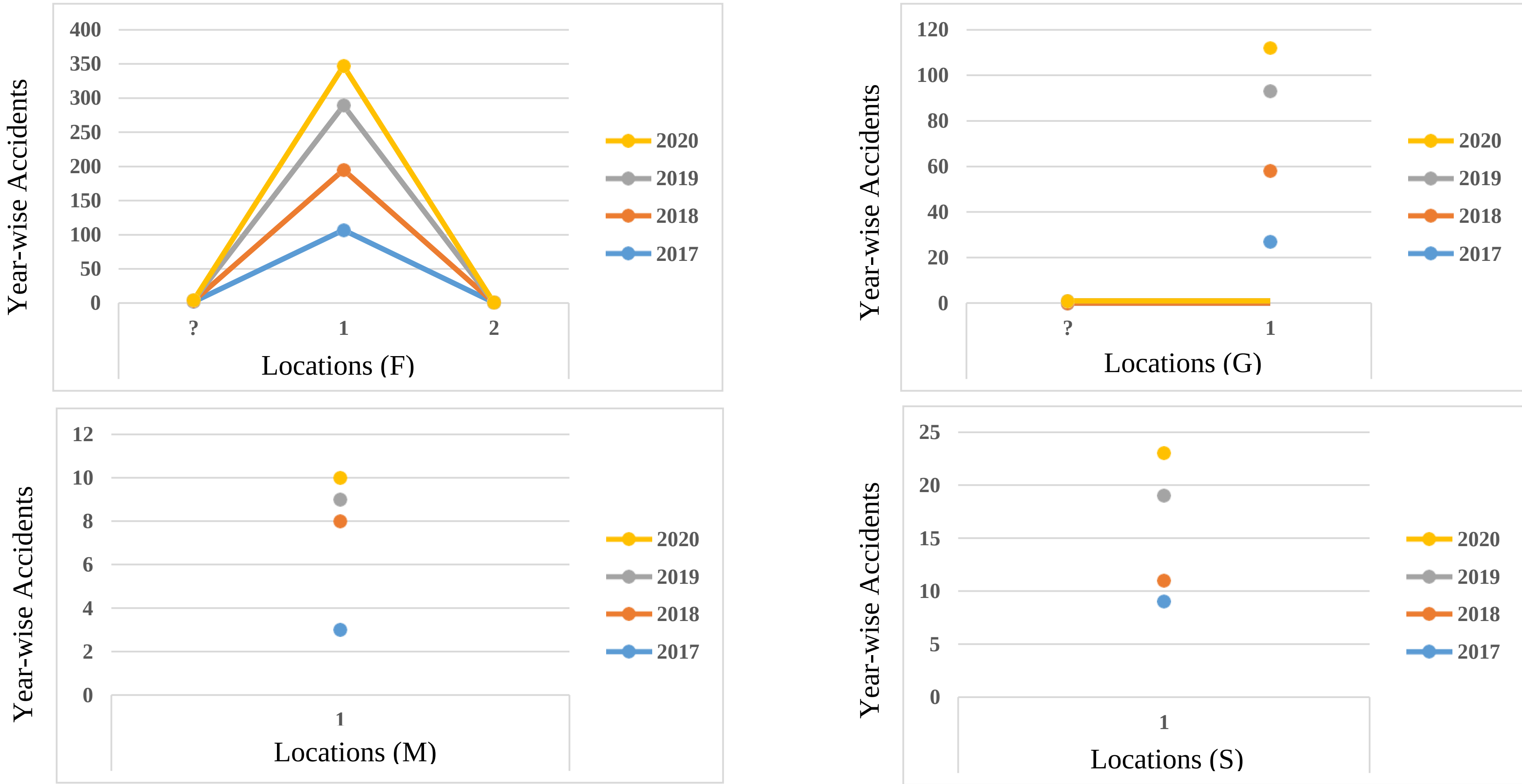
(Note: In the above figure, 1, 2, 3, 4, 5, and 6 stand for National highway, Regional highway, Feeder road, Rural road, City road, and ?/Blank data field, respectively).

Fig. 4-11: Trend of year-wise accidents at different road classes.



(Note: In the above figure, 1, 2, 3, 4, 5, and 6 stand for None, Bridge, Culvert, Narrowing/Restriction, Speed breakers, and ?/Blank data field, respectively).

Fig. 4.12: Trend of year-wise accidents at different road features.



(Note: In the above figure, 1, 2, and 3 stand for Urban area, Rural area, and?/Blank data field, respectively).

Fig. 4.13: Trend of year-wise accidents at different locations.

CHAPTER 5
DATA ANALYSIS AND MODELSELECTION

5.1 Introduction

In this chapter, the four crash severity models, namely: Multinomial Logit (MNL), Ordered Logit (OL), Ordered Probit (OP), and Partial Proportional Odds (PPO) as well as the data used in this analysis are primarily discussed along with the results of their application. Additionally, there are insights into model selection based on appropriate parameters at the end of this chapter.

5.2 Data Collection

The Accident Research Institute (ARI), Bangladesh University of Engineering and Technology (BUET), and police-reported public bus crash data from 2017 to 2020 were the sources of the data for this study. ARI employs the Microcomputer Accident Analysis Package Five (MAAP5) software to store and analyze accident data. On the other side, R, the main program utilized in this work, is incompatible with the data format of MAAP5. In order to aid in the research, ARI provided a modified Excel file of the public bus crash data.

5.3 Data Processing

At the beginning of the data processing, incomplete and inaccurate records were removed, leaving a total of 498 public bus crashes. The distribution of the observed injury severity caused by public transportation in the final sample is as follows: Fatal Injury (F): 352 (70.68%); Grievous Injury (G): 113 (22.6%); Simple Injury (S): 33(6.72%). It is worth mentioning that the data is largely dominated by accidents with fatal injuries and the proportions of simple injuries, and the motor collisions are much lower. This is a major limitation of this research as the outcome of the analysis is expected to be biased towards fatal injury accidents. In an intention to aid the analysis, the simple injury, and the motor collision accidents were aggregated into a single injury severity level and were named as simple injury. Hence, the modified crash severity level becomes: Simple Injury$(y = 1)$, Grievous Injury$(y = 2)$; and Fatal Injury$(y = 3)$.

The independent variables used in this research include temporal characteristics, roadway characteristics, environmental characteristics, crash type, etc. It is to be noted that the independent features are all nominal, and any category of a variable sharing less than 4% of the data compared to other categories in that variable is coded as other types. However, all the independent variables were not used in the analysis work; rather the entire dataset was scrutinized based on the AIC value, and some of the features were omitted to better assist the analysis work.

5.4 Descriptive Analysis

The Accident Research Institute (ARI), BUET, provided a four-year (2017-2020) police-reported database containing 498 public transportation crash data. The database's observed injury level is distributed as follows: Fatal Injury (F): 352 (70.68%), Grievous Injury (G): 113 (22.6%), and Simple Injury (S): 33 (6.72%). It is worth noting that the data is driven by fatal injury accidents, with the proportion of simple injury being substantially smaller. This is a significant limitation of this study because the results of the analysis are predicted to be biased toward fatal injury accidents. Crash characteristics, roadway attributes, environmental elements, temporal characteristics, vehicle features, and driver features are all included in the database. Based on the AIC value, variables linked to vehicle attributes and driver features were not employed in the modeling process. The variables used in the modeling process are summarized in Table 5-1. Using the database, this study developed four models: MNL, OL, OP, and PPO.

Table 5-1: Descriptive Analysis

Variable	Variable Description	Frequency	Ratio (%)
Target Variable			
Injury Severity	1 – Simple injury	33	6.72
	2 – Grievous Injury	113	22.60
	3 – Fatal Injury	352	70.68
Explanatory Variables			
Crash Characteristics			
Collision Type	1 if a rear end or head on collision	104	20.82
	1 if a hit pedestrian Collison	306	61.49
	1 if other types of collision	88	17.68

Variable	Variable Description	Frequency	Ratio (%)
Roadway Characteristics			
Junction	1 if no junction was present	256	51.77
	1 if junction was present	242	48.72
Traffic Control	1 if no traffic control system is present	116	23.38
	1 if any traffic control system is present	382	76.62
Movement	1 if the road was one way	256	51.47
	1 if the road was two-way	242	48.52
Divider	1 if no divider was present	114	22.99
	1 if divider was present	384	77.01
Surface type	1 if the road surface was sealed	493	99.02
	1 if the road surface was not sealed	5	0.98
Surface quality	1 if the road surface was good	471	94.50
	1 if the road surface was not good	27	5.50
Road Geometry	1 if the road was not straight	44	8.84
	1 if the road was straight	454	91.16
Road Class	1 if the road is a city road	221	44.40
	1 if the road is a national road	235	47.15
	1 if the road is a regional road	42	8.48
Environment Characteristics			
Light Condition	1 if during dawn/dusk	73	14.73
	1 if there was daylight	264	53.04
	1 if there was dark	161	32.22
Temporal Characteristics			
Day of Week	1 if the day was a weekday	361	72.49
	1 if the day was a weekend	137	27.50
Time	1 if during night hours	161	32.22
	1 if during off-peak hours	122	24.55
	1 if during morning peak hours	122	24.55
	1 if during afternoon peak hours	93	18.66

5.5 Results of Model Estimation

Using the accident information gathered from ARI and BUET, four crash severity models were created. The goal was to find the model that could match the given flawed data most effectively. However, in order to satisfy this aim, triggering elements that affect crash severity levels had to be found. Normally, a confidence level of 95% is used to determine the significance of any coefficients, but given the sparse set data structure obtained from ARI, this confidence level didn't work well for our models. As a result, characteristics were considered significant for each model if their p-value was less than or equal to 0.20 (i.e., a p-value $\leq$ 0.20), which corresponds to 80% confidence interval. Additionally, a conviction was established that states that if any category of an independent variable was found to be statistically significant, then that variable as a whole was considered significant in influencing injury severity of public bus crashes. This conviction was established for a clear exposition of the results, since all of the factors will decide on the selected triggering factors.

5.5.1 Application of the MNL Model

5.5.1.1 Interpretation of Result

The MNL model was applied to the crash data considering the nominal nature of accident severity. The estimation results of the MNL model are presented in Table 5.2. It is to be noted that the table has two parts: a set of results for grievous injury crashes, and a set of results for fatal injury crashes. For this study, the coefficients of simple injury crashes were restricted to zero (i.e., base outcome level). The estimated coefficients thus indicated the relative effects of contributing features on grievous, and fatal injury severity compared to simple injury severity; hence, a positive sense of coefficients will indicate an increased likelihood of severity level, and a negative sign will minimize the likelihood of severity level compared to simple injury severity. However, confusion might arise at the time of evaluating the results as all the features (viz., categorical explanatory variables) have a base category of their own. For simplicity, the interpretation will be established based on the feature base category only; although, this doesn't change the fact that the base category of crash severity is simple injury.

Table 5-2: Estimation Results of Multinomial Logit Model

	Grievous	**Std error**	**P value**	**Fatal**	**Std error**	**P value**
(Intercept)	-0.831	1.933	0.667	- 2.824	1.899	0.137**
Day of Week (Weekdays)	0.061	0.56	0.913	0.143	0.511	0.78
Time (Off Peak)	-0.221	0.978	0.821	- 0.264	0.942	0.779
Time (Morning Peak)	-1.985	0.971	0.041***	- 1.013	0.907	0.264
Time (Night)	-1.507	0.985	0.126*	- 1.116	0.937	0.233
Junction (Yes)	-0.793	0.545	0.145**	- 0.359	0.499	0.472
Traffic Control (Yes)	0.631	0.58	0.277	0.657	0.52	0.207
Collision type (Head on or Rear End)	-0.054	0.617	0.931	-0.18	0.518	0.729
Collision type (Hit Pedestrian)	2.412	0.79	0.002***	2.523	0.733	0.001***
Movement (One Way)	1.081	0.552	0.05***	0.553	0.505	0.274
Divider (Yes)	-0.098	0.634	0.877	- 0.198	0.573	0.729
Light (Day light)	-0.361	0.809	0.655	- 0.288	0.754	0.702
Light (Night)	-0.47	0.869	0.589	0.155	0.801	0.847
Road Geometry (Straight + Flat)	1.017	0.719	0.158*	1.374	0.629	0.029***
Surface type (Sealed)	0.643	1.502	0.669	2.11	1.533	0.169*
Surface Quality (Good)	0.261	0.834	0.754	1.309	0.801	0.102**
Road Class (City)	0.49	0.839	0.559	0.357	0.738	0.629
Road Class (National)	0.08	0.865	0.926	0.547	0.759	0.472

No of Observation	498
Log-likelihood at convergence	-237.171
AIC	546.3413
BIC	688.4705
*Significant at 0.05, **Significant at 0.15, ***Significant at 0.20, Base Level=Simple Injury or Motor Collision	

In an intention to assess the estimated coefficients, Table 5.2 shows that morning-peak hours are less vulnerable duration compared to afternoon peak hours, minimizing the likelihood of both grievous injury (coefficient= -1.985) and fatal injury (coefficient= -1.013); although, the feature is only statistically significant for grievous injury. During the night-time, vulnerability to grievous (coefficient= -1.507, significant feature) and fatal (coefficient= -1.116) injury decreases. This result quite coincides with the work of (Ulfarsson and Mannering, 2004) that says after dark the likelihood of fatal injury crashes reduces. On the other hand, off-peak hours are found to reduce the likelihood of grievous injury crashes; however, these results are not statistically significant.

An interesting finding is that the combined effect of traffic control (viz., centreline marking, pedestrian control, traffic lights, police+traffic lights, stop/give way sign, etc.) escalates both grievous and fatal injury, compared to no traffic control, because even at traffic-controlled regions, drivers tend to display an indifferent attitude towards the traffic rules.

Again, public buses are more prone to both grievous and fatal injury hitting pedestrians to a much significant extent. Straight and flat roads increase both types of injury compared to other road geometry, because of less precautions and over speeding of the drivers. A noticeable finding is that good surface quality of pavements escalates fatal injury crashes (coefficient= 1.309), due to the over speeding tendency of the drivers, being a statistically significant feature.

5.5.2 Application of the OL Model

5.5.2.1 Interpretation of Result

The ordinal nature of accident severity was considered while applying the OL model to crash data. It is worth mentioning that a positive (negative) value of a parameter, associated with a positive increase in the feature, will increase (decrease) the probability of the highest ordered injury severity level (i.e., fatal injury) and decrease (increase) the probability of lowest ordered injury severity (i.e., simple injury).

The explanatory variables with positive parameters in Table 5.3, like hit pedestrian type collision (coefficient= 0.744) are more likely to be involved in a fatal accident compared to a simple accident.

Moreover, a set of independent variables with positive coefficients include straight and flat road geometry, good surface conditions (Garrido et al., 2014), sealed surface types are found to be statistically significant. Public bus operation conditioned on any of these features is more likely to increase the probability of fatal injury.

For example, the likelihood of fatal injury crashes increases to a great extent (coefficient= 1.3) in sealed type surface and on dry surface quality roads (coefficient= 1.127). Again, the presence of dividers (coefficient = -0.193) and two-way movement of roads (coefficient = -0.173) alleviates fatal injury crashes compared to no dividers and one-way movement respectively.

Table 5-3: Estimation Results of Ordered Logit Model

	Estimate	Std error	t value	P value
Day of week (Weekdays)	0.194523	0.273721	0.710661	0.477294
Time (Off Peak)	0.04454	0.367984	0.121039	0.903661
Time (Morning Peak)	0.430776	0.396188	1.087302	0.276903
Time (Night)	0.170186	0.388983	0.437514	0.661739
Junction (Yes)	0.134149	0.249246	0.538217	0.590427
Traffic Control (Yes)	0.240333	0.293843	0.817897	0.413416

Collision type (Head On or Rear End)	-0.08233	0.360436	-0.22842	0.819321
Collision type (Hit Pedestrian)	0.744208	0.325409	2.286993	0.022196***
Movement (One Way)	-0.1737	0.255511	-0.67983	0.496614
Divider (Yes)	-0.19344	0.313825	-0.61638	0.537642
Light (Daylight)	-0.08027	0.380493	-0.21096	0.832917
Light (Night)	0.412351	0.419234	0.983581	0.325321
Road Geometry (Straight + Flat)	0.847304	0.393971	2.150677	0.031502***
Surface type (Sealed)	1.299997	0.895022	1.452474	0.14637**
Surface Quality (Good)	1.127085	0.455013	2.477041	0.013248***
Road Class (City)	0.040652	0.452958	0.089748	0.928487
Road Class (National)	0.55902	0.460276	1.214532	0.224545
Threshold (S->G)	1.348393	1.102854	1.222639	0.221466
Threshold (G->F)	3.05878	1.110815	2.753636	0.005894***
No of Observations	498			
Log-likelihood at Convergence	-253.604			
AIC	545.2084			
BIC	620.2211			
*Significant at 0.05, **Significant at 0.15, ***Significant at 0.20, Base Level=Simple Injury or Motor Collision				

Interpreting the coefficients in Table 5.3 is difficult as the effect of explanatory variables on any severity level in between the lowest and highest severity level cannot be explained. In our case, this abstruse severity level is grievous injury. This limitation can be interpreted by using marginal effect which explains all three severity levels individually.

5.5.2.2 Brant Test of OL Model

A primary assumption of the proportional odds (PO) model is that all features follow parallel lines assumption. However, that is not the case as some of the features are often found to be flexible, rejecting parallel line assumption. Brant test is mainly conducted to check the plausibility of the OL model maintaining parallel lines assumption. The null hypothesis of the test is that the OL model follows parallel lines assumption which is then evaluated using Chi-square test.

The results of Brant test are provided in Table 5.4, which states that altogether the parallel lines assumption has been relaxed for the proposed OL model. Furthermore, the individual features rejecting the assumption are: Time (Morning Peak), Collision type (Hit Pedestrian), and Movement (One way).

Table 5-4: Brant Test for Ordered Logit Model

	Chi-square	df	P value
Omnibus	28.71914	17	0.037205
Day of week (Weekdays)	0.008708	1	0.925652
Time (Off Peak)	0.065849	1	0.797479
Time (Morning Peak)	4.21519	1	0.040064
Time (Night)	2.43075	1	0.118976
Junction (Yes)	2.121865	1	0.14521
Traffic Control (Yes)	1.053301	1	0.304748
Collision type (Head On or Rear End)	0.01743	1	0.894966
Collision type (Hit Pedestrian)	7.746898	1	0.00538
Movement (One Way)	4.087378	1	0.043205
Divider (Yes)	1.4E-05	1	0.997011
Light (Daylight)	0.128902	1	0.719573
Light (Night)	0.361256	1	0.547809
Road Geometry (Straight + Flat)	1.406965	1	0.235561
Surface type (Sealed)	0.00605	1	0.938003
Surface Quality (Good)	0.071563	1	0.789074
Road Class (City)	0.444318	1	0.505046
Road Class (National)	0.003516	1	0.952716

5.5.3 Application of the OP Model

5.5.3.1 Interpretation of Result

The ordinal nature of accident severity was considered while applying the OP model on crash data exactly like the OL model. It is worth mentioning that a positive (negative) value of a parameter, associated with a positive increase in the feature, will increase (decrease) the probability of the highest ordered injury severity level (i.e., fatal injury) and decrease (increase) the probability of lowest ordered injury severity (i.e., simple injury).

The explanatory variables with positive parameters in Table 5.5, like hit pedestrian type collision (Coefficient= 0.49) are more likely to be involved in a fatal accident compared to a simple accident.

Moreover, a set of independent variables with positive coefficients include straight and flat road geometry ,good surface conditions (Garrido et al., 2014) are found to be statistically significant. Public bus operation conditioned on any of these features is more likely to increase the probability of fatal injury.

For example, the likelihood of fatal injury crashes increases to a great extent (coefficient= 0.499) in straight and flat roads and on dry surface quality roads (coefficient= 0.63).

Again, the presence of dividers (coefficient = -0.098) and two-way movement (coefficient = -0.056) are likely to alleviate fatal injury crashes compared to no dividers and one-way movement respectively.

Table 5-5: Estimation Results of Ordered Probit Model

	Estimate	Std error	t value	P value
Day of week (Weekdays)	0.09242	0.157982	0.585006	0.558544
Time (Off Peak)	0.020444	0.214721	0.09521	0.924148
Time (Morning Peak)	0.184373	0.224993	0.819461	0.412523
Time (Night)	0.065037	0.221817	0.293202	0.769368
Junction (Yes)	0.058424	0.142022	0.41137	0.680801
Traffic Control (Yes)	0.137549	0.166072	0.828249	0.407529
Collision type (Head on or Rear End)	-0.03555	0.205169	-0.17329	0.862427
Collision type (Hit Pedestrian)	0.492884	0.18475	2.667847	0.007634***
Movement (One Way)	-0.05656	0.145395	-0.38902	0.697263

Divider (Yes)	-0.09886	0.1752	-0.56428	0.572561
Light (Daylight)	-0.0576	0.219767	-0.2621	0.793245
Light (Night)	0.200251	0.240574	0.83239	0.405189
Road Geometry (Straight + Flat)	0.499322	0.228814	2.182221	0.029093***
Surface type (Sealed)	0.719696	0.566409	1.27063	0.20386
Surface Quality (Good)	0.63636	0.276424	2.30212	0.021328*
Road Class (City)	0.061823	0.256155	0.241349	0.809285
Road Class (National)	0.333012	0.259341	1.284074	0.199116*
Threshold (S->G)	0.789447	0.672198	1.174426	0.240224
Threshold (G->F)	1.725893	0.675722	2.554147	0.010645***
No of Observations	498			
Log-likelihood at Convergence	-252.921			
AIC	543.8425			
BIC	618.8551			
*Significant at 0.05, **Significant at 0.15, ***Significant at 0.20, Base Level=Simple Injury or Motor Collision				

Interpreting the coefficients in Table 5.5 is same as the OL model. This limitation can be interpreted by using marginal effect which explains all three severity levels individually.

5.5.4 Application of the PPO Model

5.5.4.1 Result Interpretation

The PPO model was developed relaxing all the features that rejected parallel lines assumption in Brant test, and restricting all other features that supported the assumption. Estimation results of the PPO model are shown in Table 5.6. The findings of the PPO model are actually a series of binary logits. In interpreting the results from Table 5.6, the current and all the lowest coded severity levels are considered the base group i.e., for any level i $(1 < i < 1)$, categories 1 to i are coded as zero (i.e., base group) and categories $i + 1$ to I are coded as one. Therefore, a positive (negative) coefficient will denote an increased (decreased) likelihood of the higher severity level compared to the base severity level. It is worth mentioning that preceding discussion was for the features that rejected parallel lines assumption, and all the other features can be explained following the evaluation technique of the OL and OP models.

Table 5.6 presents the estimation result in three parts: All level; 2, 3 vs 1; and 3 vs 1, 2. It is to be noted that in the table 1 stands for simple injury, whereas 2, and 3 represents grievous, and fatal injury, respectively. All section contains the estimation result of all those explanatory features that follows the parallel lines assumption, and the other two parts shows the result of those features that rejected the parallel lines assumption.

Table 5-6: Estimation Results of Partial Proportional Odds Model

	All level			2,3 vs 1			3 vs 1,2		
Variables	Coeff.	S.E.	P-val.	Coeff.	S.E.	P-val.	Coeff.	S.E.	P-val.
Intercept				-1.789	1.167	0.125**	-2.962	1.153	0.01***
Time (Morning Peak)				-0.285	0.504	0.572	0.534	0.398	0.18*
Collision type (Hit Pedestrian)				2.371	0.663	0***	0.608	0.328	0.064**
Movement (One Way)				0.319	0.435	0.463	-0.26	0.259	0.314
Day of week (Weekdays)	0.163	0.273	0.55						
Junction (Yes)	0.152	0.25	0.542						
Traffic Control (Yes)	0.228	0.293	0.435						
Divider (Yes)	-0.178	0.313	0.569						
Light (Daylight)	-0.093	0.381	0.808						
Light (Night)	0.41	0.42	0.328						
Road Geometry (Straight + Flat)	0.798	0.397	0.044***						
Surface type (Sealed)	1.446	0.95	0.128**						
Surface Quality (Good)	1.049	0.462	0.023***						
Road Class (City)	0.043	0.451	0.924						
Road Class (National)	0.562	0.46	0.221						
Time (Off. Peak)	0.036	0.369	0.922						
Time (Night)	0.182	0.388	0.639						

Collision type (Head On or Rear End)	-0.102	0.358	0.776						
No. of observation	498								
Log-likelihood at convergence	-242.387								
AIC	528.7741								
BIC	615.6309								

The estimation result of 'movement (one way)' in Table 5.6 can be elucidated as follows: the positive coefficient of 0.319 indicates that any public bus operating on one way road compared to two way road is more likely to result a fatal, or a grievous injury than a simple injury; the other coefficient of -0.26 implies that for the same condition applied, the vehicle is less likely to generate a fatal injury than a simple or a grievous injury. This result is perceptible as one-way roads are more vulnerable to head-on crashes.

5.6 Comparative Study

The model performances were compared in terms of the log-likelihood (LL) of the full model, AIC, and BIC values. Table 5.7 presents the result of the concerned parameters.

Table 5-7: Results in Terms of Comparison Criterion

Comparison Parameters	Models			
	MNL	OL	MNL	PPO
LL	-237	-254	-253	-242
AIC	546	545	544	529
BIC	688	620	619	616

The parameter values in Table 5.7 are a bit perplexing to raise any explicit inference to this analysis work. It was found that the MNL model is most effective compared to other models in terms of log-likelihood, PPO is most effective in terms of AIC and BIC.

The models were further compared based on the significance of their predictors (Table 5.8). In this case, if any category of an independent variable was found to be statistically significant, then that entire variable was considered significant in influencing the injury severity of public bus crashes. However, as per the degree of significance, collision type, road geometry and surface quality are considered to be the most significant ones; whereas, surface type and time are considered to be significant too. In this regard, junction type, road class and movement bear a least significance, since they had produced a formidable value for one particular model only. Both the MNL and PPO models have almost the same number of significant features impacting public bus crash injury severity. Hence, MNL and PPO models are considered to be more robust compared to others in the context of the available crash data in Dhaka city.

Table 5-8: Results in Terms of Significant Predictors

Predictors	Models			
	MNL	OL	OP	PPO
Collision Type	✓	✓	✓	✓
Junction Type	✓			
Movement	✓			
Road Class			✓	
Road Geometry	✓	✓	✓	✓
Surface Quality	✓	✓	✓	✓
Surface Type	✓	✓		✓
Time	✓			✓

5.7 Summary of Comparison

Table 5-9: Summary of Comparison

Name of Models	Factor Significance								Comparison Parameters		
	Collision Type	Junction Type	Movement	Road Class	Road Geometry	Surface Quality	Surface Type	Time	LL	AIC	BIC
MNL	✓	✓	✓		✓	✓	✓	✓	-237	546	688
OL	✓				✓	✓	✓		-254	545	620
OP	✓			✓	✓	✓			-253	544	619
PPO	✓				✓	✓	✓	✓	-242	529	616

CHAPTER 6
CONCLUSIONS

6.1 General

This thesis is one of the pioneers to use a set of recognized statistical modeling techniques to investigate public bus safety in Bangladesh. By using four different crash severity models on the collision data that was available in Bangladesh, the goal of this study was to identify the high impact variables relating to public bus safety.

6.2 Key Findings of this Study

This study's key result is that the existing accident severity models have revealed several important and startling truths from crash data involving public buses. Comparatively, these derived facts and specifics are more helpful in improving the understanding of accident situation in Bangladesh than the earlier descriptive-based approaches. The important conclusions of this thesis are as follows:

a) Public buses striking pedestrians were highly significant in escalating grievous and fatal harm when compared to all other accident kinds, such as head-on, rear-end, side swipe, etc. This outcome is unsurprising, given that a collision between a public bus and a pedestrian can only result in fatalities due to the vast disparity in their bodily masses.

b) Two-way roads were seen to be significantly safer than one-way roads. Again, a divider between the lanes was found to reduce the risk of fatal injuries, and a two-way road without one is more likely to have head-on collisions, which are more likely to end in fatalities.

c) Straight and flat road geometry with good surface quality are found to escalate public bus fatalities in Dhaka city. The outcome becomes more severe when public bus operates on a sealed surface, instead of brick or earthen one. The result is foreseeable due to the absence of necessary safety parameters on Dhaka city road networks.

d) Public buses operating on national roads are found to trigger more fatal injuries. However, the presence of junctions in this regard, is considered as useful in reducing grievous injury severities.

e) It was discovered that light condition during the daylight and at night (unlit) time increased the severity of public bus crashes significantly. Additionally, the likelihood of deadly accidents increased at night when there were no street lights.

f) Comparative analysis also showed that the MNL model is found to be more robust in terms of selected comparison parameters. MNL and PPO, both models yielded almost about the same number of significant predictors when compared to one another, despite the modest differences in the significance of the essential components for these models. The MNL performed better than other models based on log-likelihood, while PPO fared better based on AIC and BIC, respectively, which led to the final model selection decision.

6.3 General Recommendations

The ability to infer useful recommendations from the study's findings is the most important quality of any analysis-based activity. The four independent severity models calculated high impact variables triggering public bus safety in Dhaka as mentioned in section 6.2 of this chapter. These facts, however, do not offer a convincing justification for Bangladesh's Public Bus safety status. As a result, more consideration is needed before the findings can be used to create policy. Examples of the origins and treatment that are relevant to the findings include the following:

a) Pedestrians struck by public buses result in the deadliest consequences. Furthermore, in rural locations, pedestrians are more at risk. This statistic emphasizes how vulnerable pedestrians are in remote regions without adequate pedestrian facilities. Additional pedestrian facilities, such as crosswalks, waiting areas, overpasses, etc., to be provided to both the regions in order to resolve this issue.

b) A two-way road without a divider in the middle is more fatality-prone than a two-way road with a divider in-between. This suggests building dividers in two-way streets since they will significantly reduce the likelihood of head-on crashes.

c) Straight and flat stretches of road lure drivers into over speeding and resulting unwanted fatalities for the pedestrians. However, this tendency gets more conspicuous when they operate on a good and sealed road surface. In this regard, physical separation of pedestrians from the vehicular traffics is of utmost importance. Provision of junction at places and marking of roadway with necessary traffic signs viz. warning signs, speed limit signs, mandatory signs etc., will be useful in arresting the speed of vehicular traffics on roadway.

d) Public bus crash injury severity is also suffered by night-time (unlit condition) driving where the street lights are inadequate. Provision of using retro-reflective roadway markings and arranging adequate lights on the streets may be useful to resolve this issue. However, drivers' understanding of night-time glare-control and undergoing regular medical check-up (especially, for the eye-sight) will be handy in reducing the likelihood of public bus related crashes.

6.4 Limitations of this Study

a) A number of features in the FIR report, including geometric features, environmental features, vehicle-related features, driver-related features, pedestrian-related features, and others are used to exploit the severity of collision injuries. In this study, the four severity models were trained using only geometric and environmental variables. This idea was taken into account in order to simplify data analysis. The study's fundamental flaw is the exclusion of other features, despite the fact that this strategy improved assessment of the relevant qualities.

b) Owing to the discrete nature of response variable, the approaches chosen for this thesis are well-established and effective. However, these approaches are a little out of date given the recent boom in data science. Additionally, the assumptions of these selected approaches severely restrict the effectiveness of crash severity modeling. On the other hand, by using sophisticated modeling techniques, this can be easily avoided. However, the objective was to assess how these fundamental and well-known models functioned on the crash data that was available in Bangladesh and, if necessary, to recommend further cutting-edge approaches.

c) Any study's analysis generally uses a confidence level of 95–99%. However, the model didn't perform well with this degree of confidence level due to the little quantity and quality of data that we acquired from ARI. Because of this, the 80% confidence threshold was used resulting in less precise predictions.

6.5 Future Scope

a) Geometric and environmental characteristics are the only predictors utilized in this study. However, in order to gain a better understanding of the situation of public bus safety in Bangladesh, vehicle-related features, driver-related features, pedestrian-related features, and other factors are also necessary.

b) On the same crash data (2017–2020) utilized in this thesis, advanced modeling techniques, including artificial neural networks, heteroskedastic ordered logit/probit, nested logit, random parameters (mixed) logit/ordered logit etc. can be applied. After that, the accuracy of these algorithms using appropriate comparison parameters can be tested.

c) Since accident severity was the target/dependent predictor, the study's main focus was on how accident severity is related to the road, roadway, and operational environment. However, new connections can be discovered as a result of changing the target predictor to any other variables, such as accident/collision type, road class etc. and draw new relationships accordingly.

d) The aspect of collecting the least severe crash records requires special attention.

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ANNEXURE

Anx.1: Accident Research Form (1/2)

Form No. 34
Bengal Form No. 403Q

1. দূর্ঘটনার ক্রমিক নম্বর	গণপ্রজাতন্ত্রী বাংলাদেশ সরকার বাংলাদেশ পুলিশ সড়ক দূর্ঘটনার রিপোর্ট ফরম Regulation 254 (b)	3. থানা
2. প্রাথমিক তথ্য বিবরণী নম্বর		4. জিলা / মেট্রো পুলিশ
5. দূর্ঘটনা কবলিত গাড়ীর সংখ্যা 6. হতাহত ড্রাইভারের সংখ্যা 7. হতাহত যাত্রীর সংখ্যা 8. হতাহত পথচারীর সংখ্যা	9. দূর্ঘটনার মাত্রা F. মৃত্যু ঘটিত দূর্ঘটনা G. মারাত্মক ক্ষত জনিত দূর্ঘটনা S. সাধারন ক্ষত জনিত দূর্ঘটনা M. মটর সংঘর্ষ	দূর্ঘটনার তারিখ 11. তারিখ 12.মাস 13.বছর --------- / ---------- / ----------- 14. দূর্ঘটনার সময় রিপোর্ট করার তারিখ
	10. দিন [সোম, মঙ্গল, বুধ, বৃহস্পতি, শুক্র, শনি, রবি] 1 2 3 4 5 6 7	রিপোর্ট করার সময়

15. সংযোগ স্থলের ধরণ
1. সংযোগ স্থল নয়
2.
3.
4.
5.
6. রেলওয়ে ক্রসিং
7. অন্যান্য ---------

16. ট্রাফিক নিয়ন্ত্রণ ব্যবস্থা
1. অনিয়ন্ত্রিত
2. রোড ডিভাইডার দ্বারা নিয়ন্ত্রিত
3. পথচারী পারাপার
4. পুলিশ নিয়ন্ত্রিত
5. ট্রাফিক বাতি নিয়ন্ত্রিত
6. পুলিশ ও ট্রাফিক বাতি নিয়ন্ত্রিত
7. থামা / যেতে দিন সংকেত দ্বারা নিয়ন্ত্রিত
8. অন্যান্য -------

17. সংঘর্ষের ধরন
1. মুখোমুখি
2. পশ্চাদ ভাগ
3. সমকোন
4. পার্শ্ব ঘর্ষণ
5. উল্টে যাওয়া
6. রাস্তার উপরস্থ বস্তুকে আঘাত
7. রাস্তার ধারের বস্তুকে আঘাত
8. দাঁড়ানো গাড়ীকে আঘাত
9. পথচারীকে আঘাত
10. জন্তুকে আঘাত
11. অন্যান্য ----(যেমন গাড়ীর ছাদ থেকে পড়ে যাওয়া)

18. গাড়ী চলাচলের দিক
1. এক মুখী চলাচল
2. উভয়মুখী চলাচল

19. রোড ডিভাইডার
1. আছে
2. নাই

20. আবহাওয়া	21. আলো	22. রাস্তার জ্যামিতিক বিবরণ	23. রাস্তার উপরিভাগের অবস্থা	24. রাস্তার প্রকারভেদ	25. রাস্তার প্রকৃতি	26. রাস্তার শ্রেনী
1. ভাল	1. দিন	1. সোজা - সমতল	1. শুকনা	1. পাকা	1. ভাল	1. ন্যাশনাল
2. বৃষ্টি	2. ভোর / সন্ধ্যা	2. বাঁকানো	2. ভেজা	2. ইটের রাস্তা	2. এবড়ো থেবড়ো (রাফ)	2. রিজিওনাল
3. ঝড়	3. আলোকিত সড়ক (রাতে)	3. অসমতল	3. কর্দমাক্ত	3. কাঁচা	3. মেরামত কাজ চলছে	3. ফিডার রোড
4. কুয়াশা	8. অনালোকিত সড়ক (রাতে)	4. বাঁকা- অসমতল	4. জলমগ্ন /প্লাবিত			4. রুরাল রোড
		5. চুড়া	5. অন্যান্য			5. সিটি রোড

27. রাস্তার বৈশিষ্ট্য	28. এলাকার ধরন	অফিসে ব্যবহারের জন্য			
1. সাধারণ রাস্তা 2. সেতু 3. কালভার্ট 4. সংকীর্ণ / বাধা প্রাপ্ত 5. স্পীড ব্রেকার	1. শহর 2. গ্রাম এলাকা		29. XY MAP 30. X 31. Y	32. ROUTE 33. KM 34. 100m	35. NODE MAP 36. NODE 1 37. NODE 2

অবস্থান
নগর/শহর/গ্রাম এর নাম...থেকে দুরত্ব :------------------------------(কি: মি/মি)

রাস্তার নাম : .... মধ্যে — রোড / স্থান (১)..................................দুরত্ব : ------------------------------(কি: মি/মি)
রোড / স্থান (২)..................................দুরত্ব : ------------------------------(কি: মি/মি)

দ্বিতীয় রাস্তার নাম (শুধু মাত্র সংযোগ স্থানের দূর্ঘটনার ক্ষেত্রে) : ....থেকে দুরত্ব : ------------------------------(কি: মি/মি)

দূর্ঘটনা স্থানের রেখা চিত্র : দূর্ঘটনার স্থান থেকে নিকটবর্তী কিমি পোষ্ট,সেতু বা রাস্তার সংযোগ স্থান বা অন্যান্য যে কোন স্থায়ী গুরুত্বপূর্ন স্থাপনা হইতে দুরত্ব দেখাইয়া চিত্র

সংঘর্ষের রেখা চিত্র : দূর্ঘটনা কবলিত গাড়ী / পথচারী সমূহের চলাচলের দিক এবং অবস্থান সহ সংঘর্ষের পূর্ণ চিত্র

দূর্ঘটনার সংক্ষিপ্ত বিবরণ
....

সাক্ষী
১. নাম ও ঠিকানা -------------------------------
২. নাম ও ঠিকানা -------------------------------

বিবরণ লিপিবদ্ধকারী অফিসার
নাম/ পদবি ....তারিখ

অনুসন্ধানকারী অফিসার
নাম/ পদবি ....তারিখ

তত্ত্বাবধানকারী অফিসার
নাম/ পদবি....................................তারিখ

আইনের ধারা

কেসের অবস্থা
1. চার্জসীট
2. ফাইনাল রিপোর্ট
3. তদন্তাধীন

Anx.1: Accident Research Form (2/2)

দুর্ঘটনায় ২ এর অধিক যানবাহন, ৬ এর অধিক যাত্রী অথবা ৩ এর অধিক পথচারী হতাহত হইলে অতিরিক্ত ফরমের দরকার হইবে। অতিরিক্ত ফরমে দূর্ঘটনার ক্রমিক নম্বর থানা ও জেলা/মেট্রোপুলিশ এবং দুর্ঘটনার বৎসর উল্লেখ করিয়া এক সাথে গাথিয়া দিতে হইবে।

যানবাহন ১

মালিকের নাম

মালিকের ঠিকানা

যানবাহন প্রস্তুতকারী

রেজিষ্ট্রেশন নম্বর: 38. জেলা 39. নম্বর

40. বৈধ ফিটনেস সার্টিফিকেট 1. আছে 2. নাই 3. প্রযোজ্য নয়

বীমা কৃত 1. ৩য় পার্টি 2. কম্প্রিহেনসিভ

41. যানবাহনের ধরণ
1. বাইসাইকেল
2. রিকসা / ভ্যান
3. ঠেলাগাড়ী
4. মটর সাইকেল
5. বেবী টেক্সী/CNG
6. টেম্পো
7. মাইক্রোবাস
8. মিনি বাস
9. বাস
10. কার
11. জীপ
12. পিক আপ
13. ছোট ট্রাক
14. ভারী ট্রাক
15. অর্টিকুলেটেড ট্রাক
16. ট্যাংকার
17. ট্রাক্টর
18. পশু চালিত
19. অন্যান্য ---- (নসিমন/ করিমন ইত্যাদি)

42. যানবাহন চলাচলের ধরণ
1. বামে মোড়
2. ডানে মোড়
3. 'U' মোড়
4. সম্মুখে স্থলে আড়াআড়ি অতিক্রম
5. ওভারটেকিং
6. সোজাসুজি চলা
7. পিছনের দিকে চলা
8. হঠাৎ যাত্রা করা
9. হঠাৎ থামা / গতি কমানো
10. পার্ক/দাঁড়ানো অবস্থায়
11. অন্যান্য -------------

43. যানবাহনের মালামাল বোঝাই
1. আইনানুগ
2. বেআইনী/ বিপজ্জনক বোঝাই

44. যানবাহনের ত্রুটি
1. ত্রুটি মুক্ত
2. লাইট
3. ব্রেক
4. ষ্টিয়ারিং
5. টায়ার
6. বহুবিধ
7. অন্যান্য ---------

45. যানবাহনের ক্ষতি (দুর্ঘটনা জনিত)
1. নাই
2. সামনে
3. পিছনে
4. ডানে
5. বামে
6. ছাদে
7. বহুবিধ
8. অন্যান্য----------

চালক ১

নাম

ঠিকানা

ড্রাইভিং লাইসেন্স: 46. জেলা 47. নম্বর

লাইসেন্সের ধরণ এবং যানের শ্রেণী

মেয়াদ অতিক্রান্তের তারিখ

48. চালকের লিঙ্গ
1. পুরুষ
2. স্ত্রী

49. চালকের বয়স

50. চালকের ক্ষত
- F. মৃত্যু
- G. মারাত্মক ক্ষত
- S. সাধারণ ক্ষত
- N. অক্ষত

51. মদ্যপ কিনা
1. সন্দেহ আছে
2. সন্দেহ মুক্ত

52. সীট বেল্ট / হেলমেট
1. পরিহিত
2. পরিহিত নয়

যানবাহন ২

মালিকের নাম

মালিকের ঠিকানা

যানবাহন প্রস্তুতকারী

রেজিষ্ট্রেশন নম্বর: 38. জেলা 39. নম্বর

40. বৈধ ফিটনেস সার্টিফিকেট 1. আছে 2. নাই 3. প্রযোজ্য নয়

বীমা কৃত 1. ৩য় পার্টি 2. কম্প্রিহেনসিভ

41. যানবাহনের ধরণ
1. বাইসাইকেল
2. রিকসা / ভ্যান
3. ঠেলাগাড়ী
4. মটর সাইকেল
5. বেবী টেক্সী/CNG
6. টেম্পো
7. মাইক্রোবাস
8. মিনি বাস
9. বাস
10. কার
11. জীপ
12. পিক আপ
13. ছোট ট্রাক
14. ভারী ট্রাক
15. অর্টিকুলেটেড ট্রাক
16. ট্যাংকার
17. ট্রাক্টর
18. পশু চালিত
19. অন্যান্য ---- (নসিমন/ করিমন ইত্যাদি)

42. যানবাহন চলাচলের ধরণ
1. বামে মোড়
2. ডানে মোড়
3. 'U' মোড়
4. সম্মুখে স্থলে আড়াআড়ি অতিক্রম
5. ওভারটেকিং
6. সোজাসুজি চলা
7. পিছনের দিকে চলা
8. হঠাৎ যাত্রা করা
9. হঠাৎ থামা / গতি কমানো
10. পার্ক/দাঁড়ানো অবস্থায়
11. অন্যান্য -------------

43. যানবাহনের মালামাল বোঝাই
1. আইনানুগ
2. বেআইনী/ বিপজ্জনক বোঝাই

44. যানবাহনের ত্রুটি
1. ত্রুটি মুক্ত
2. লাইট
3. ব্রেক
4. ষ্টিয়ারিং
5. টায়ার
6. বহুবিধ
7. অন্যান্য ---------

45. যানবাহনের ক্ষতি (দুর্ঘটনা জনিত)
1. নাই
2. সামনে
3. পিছনে
4. ডানে
5. বামে
6. ছাদে
7. বহুবিধ
8. অন্যান্য----------

চালক ২

নাম

ঠিকানা

ড্রাইভিং লাইসেন্স: 46. জেলা 47. নম্বর

লাইসেন্সের ধরণ এবং যানের শ্রেণী

মেয়াদ অতিক্রান্তের তারিখ

48. চালকের লিঙ্গ
1. পুরুষ
2. স্ত্রী

49. চালকের বয়স

50. চালকের ক্ষত
- F. মৃত্যু
- G. মারাত্মক ক্ষত
- S. সাধারণ ক্ষত
- N. অক্ষত

51. মদ্যপ কিনা
1. সন্দেহ আছে
2. সন্দেহ মুক্ত

52. সীট বেল্ট / হেলমেট
1. পরিহিত
2. পরিহিত নয়

হতাহত যাত্রীর বিবরণ

একজন যাত্রীর জন্য একটি লাইন পুরণ করুন — * = নীচের বক্স দেখুন

নাম ও ঠিকানা	53. যানবাহন নং	54. লিঙ্গ	55. বয়স	56. * ক্ষত	57. * অবস্থান	58. * কার্যক্রম
1.						
2.						
3.						
4						
5.						
6.						

হতাহত পথচারীর বিবরণ

একজন পথচারীর জন্য একটি লাইন পুরণ করুন — * = নীচের বক্স দেখুন

নাম ও ঠিকানা	59. যানবাহন নং	60. লিঙ্গ	61. বয়স	62. * ক্ষত	63. * অবস্থান	64. * কার্যক্রম
1.						
2.						
3.						

দুর্ঘটনার সহায়ক কারণ

১. মাত্রাতিরিক্ত গতি
২. বেপরোয়া চালান
৩. চালকের ক্লান্তি
৪. সামনের গাড়ির অতি সন্নিকটে চালান
৫. চালকের ভুল সংকেত
৬. ভুল ওভারটেকিং
৭. ভুল ভাবে মোড় নেয়া
৮. মদ্যপ চালক
৯. পথচারীর কার্যক্রম
10. যাত্রীর কার্যক্রম
11. খারাপ রাস্তার জন্য
12. রাস্তার জ্যামিতিক ত্রুটি
13. আবহাওয়া
14. গাড়ীর যান্ত্রিক ত্রুটি
15. বিপজ্জনক বোঝাই
16. টায়ার বার্ষ্ট
17. পশুর কার্যক্রম
18. অন্যান্য ---------- (যেমন: রাস্তার উপর দালাদার/ পিচ্ছিল জিনিস পড়ে থাকা, গতি রোধক, দুর্বল ব্রিজ / কালভার্ট ইত্যাদির কারনে)

65. ☐☐

66. ☐☐

67. ☐☐

* 56--58 এবং 62--64 এর সহায়ক বক্স

শুধুমাত্র নমুনার জন্য বৃত্ত দিবেন না

56. যাত্রীর ক্ষত / 62. পথচারীর ক্ষত
- F. মৃত্যু
- G. মারাত্মক ক্ষত
- S. সাধারণ ক্ষত

57. যাত্রীর অবস্থান
1. গাড়ীর ভিতরে
2. গাড়ীর বাইরে
3. গাড়ীর ছাদে

58. যাত্রীর কার্যক্রম
1. নাই
2. যানে উঠিতেছিল
3. যান হইতে নামিতেছিল
4. যান হইতে পড়িয়া যাওয়া
5. অন্যান্য

63. পথচারীর অবস্থান
1. পথচারি পারাপারে
2. পারাপারের ৫০ মিঃ মধ্যে
3. সড়ক দ্বীপ / ডিভাইডারে
4. রাস্তার উপরে
5. ফুটপাতে
6. রাস্তার পাশে/ সোল্ডারে
7. বাস ষ্টপে

64. পথচারীর কার্যক্রম
1. নাই
2. রাস্তা পারাপার হওয়া
3. রাস্তার উপর দিয়ে চলা
4. রাস্তার পাশ/ সোল্ডার দিয়ে চলা
5. রাস্তার উপরে খেলা করা

Anx.2: Accident Research Form (1/2)

গণপ্রজাতন্ত্রী বাংলাদেশ সরকার
পুলিশ হেডকোয়ার্টার্স, ঢাকা।

প্রজ্ঞাপন

নং-এস, আর, ও — তারিখ :

Police Act, 1861 (V of 1861) এর section 12 এ প্রদত্ত ক্ষমতাবলে মহা-পুলিশ পরিদর্শক, সরকারের পূর্বানুমোদনক্রমে, Police Regulations Bengal, 1943 এর নিম্নরূপ অধিকতর সংশোধন করিল, যথা:-

উপরি-উক্ত Regulations এর Volume II এর B.P. Form No. 34/Bengal Form No-403Q এর পরিবর্তে নিম্নরূপ Form প্রতিস্থাপিত হইবে, যথা:-

B.P. Form No. 34
Bengal Form No. 403Q

BANGLADESH POLICE
Register of Road Traffic Accident
(REPORT FORM)
[Regulation 254(b)]

1. ACCIDENT REPORT NO.
2. FIR NO.
3. THANA
4. DISTRICT/MET. POL.

5. NUMBER OF VEHICLES INVOLVED
6. NUMBER OF DRIVER CASUALTIES
7. NUMBER OF PASSENGER CASUALTIES
8. NUMBER OF PEDESTRIAN CASUALTIES

9. ACCIDENT SEVERITY
- F. Fatal Accident
- G. Grievous Accident
- S. Simple Injury Accident
- M. Motor Collision

10. DAY

DATE OF OCCURRENCE — 11. DATE 12. MONTH 13. YEAR .... / .... / ....

14. TIME OF OCCURRENCE

Date Of Reporting

Time Of Reporting

15. JUNCTION TYPE
1. Not at Junction
2.
3.
4.
5.
6. Railway
7. Other ....

16. TRAFFIC CONTROL
1. No Control
2. Centreline
3. Pedestrian Crossing
4. Police Controlled
5. Traffic Lights
6. Police + Traffic Lights
7. Stop/Give Way sign
8. Other ....

17. COLLISION TYPE
1. Head On
2. Rear End
3. Right Angle
4. Side Swipe
5. Overturned Vehicle
6. Hit Object in Road
7. Hit Object off Road
8. Hit Parked Vehicle
9. Hit Pedestrian
10. Hit Animal
11. Other ....

18. MOVEMENT
1. 1-Way Street
2. 2-Way Street

19. DIVIDER ?
1. Yes
2. No

20. WEATHER
1. Fair
2. Rain
3. Wind
4. Fog

21. LIGHT
1. Daylight
2. Dawn/Dusk
3. Night (lit)
4. Night (unlit)

22. ROAD GEOMETRY
1. Straight + Flat
2. Curve Only
3. Slope Only
4. Curve + Slope
5. Crest

23. SURFACE CONDITION
1. Dry
2. Wet
3. Muddy
4. Flooded
5. Other ....

24. SURFACE TYPE
1. Sealed
2. Brick
3. Earth

25. SURFACE QUALITY
1. Good
2. Rough
3. Under Repair

26. ROAD CLASS
1. National
2. Regional
3. Feeder
4. Rural Road
5. City

27. ROAD FEATURE
1. None
2. Bridge ....
3. Culvert
4. Narrowing/Restriction
5. Speed Breakers

28. LOCATION TYPE
1. Urban Area
2. Rural Area

OFFICE USE ONLY

29. XY MAP
30. X
31. Y
32. ROUTE
33. KM
34. 100m
35. NODE MAP
36. NODE 1
37. NODE 2

LOCATION

Name of City/Town/Village .... Distance: .... (km/m)

Name of Road .... Between — Landmark 1 .... Distance: .... (km/m)
Landmark 2 .... Distance: .... (km/m)

JUNCTION ACCIDENT ONLY Name of SECOND Road .... Distance: .... (km/m)

LOCATION SKETCH Show site in relation to prominent landmarks such as KM posts, bridges or road intersections. Mark distances to the landmarks

COLLISION DIAGRAM SKETCH mark the position and direction of each vehicle and details of the road layout at the site of the accident

SUMMARY OF ACCIDENT
....

WITNESSES
1. Name & Address ....
....
2. Name & Address ....
....

RECORDING OFFICER
Name/Rank .... Date ....

INVESTIGATING OFFICER
Name/Rank .... Date ....

SUPERVISING OFFICER
Name/Rank .... Date ....

SECTION OF LAW

STATUS OF CASE
1. Charge Sheet
2. Final Report
3. Under Investigation

Contd P/2

Anx.2: Accident Research Form (2/2)

-2-

Additional form(s) will be needed if there are more than 2 vehicles, more than 6 passenger casualties or more than 3 pedestrian casualties
Mark each additional form with the REPORT NUMBER, THANA, DISTRICT/MET POL. and YEAR. Fix forms together

VEHICLE 1

OWNER'S NAME

OWNER'S ADDRESS

VEHICLE MANUFACTURER

VEHICLE REGISTRATION: 38. DISTRICT 39. NUMBER

40. VALID FITNESS CERTIFICATE 1. Yes 2. No 3. n/a

INSURANCE COVER 1. Third Party 2. Comprehensive

41. VEHICLE TYPE
1. Bicycle
2. Rickshaw
3. Push Cart
4. Motor Cycle
5. Baby Taxi
6. Tempo
7. Microbus
8. Minibus
9. Bus
10. Car
11. Jeep
12. Pick Up
13. Truck (<3.5t)
14. Heavy Truck
15. Artic. Truck
16. OilTanker
17. Tractor
18. Animal Drawn
19. Other ....

42. VEHICLE MANOEUVRE
1. Left Turn
2. Right Turn
3. 'U' Turn
4. Crossing Road
5. Overtaking
6. Going Ahead
7. Reversing
8. Sudden Start
9. Sudden Stop
10. Parked
11. Other ....

43. VEHICLE LOADING
1. Legal
2. Illegal/Unsafe

44. VEHICLE DEFECT (from MVI report)
1. None
2. Lights
3. Brakes
4. Steering
5. Tyres
6. Multiple
7. Other ....

45. VEHICLE DAMAGE (Sustained in accident)
1. None
2. Front
3. Rear
4. Right
5. Left
6. Roof
7. Multiple
8. Other ....

DRIVER 1

NAME

ADDRESS

DRIVING LICENSE: 46. DISTRICT 47. NUMBER

LICENSE TYPE + CATEGORY EXPIRY DATE

48. DRIVER SEX
1. Male
2. Female

49. DRIVER INJURY
F. Fatal
G. Grievous
S. Simple Injury
N. Not Injured

50. DRIVER AGE

51. ALCOHOL
1. Alcohol Suspected
2. Not Suspected

52. SEAT BELT/HELMET
1. Seat Belt/Helmet Worn
2. Not Worn

VEHICLE 2

OWNER'S NAME

OWNER'S ADDRESS

VEHICLE MANUFACTURER

VEHICLE REGISTRATION: 38. DISTRICT 39. NUMBER

40. VALID FITNESS CERTIFICATE 1. Yes 2. No 3. n/a

INSURANCE COVER 1. Third Party 2. Comprehensive

41. VEHICLE TYPE
1. Bicycle
2. Rickshaw
3. Push Cart
4. Motor Cycle
5. Baby Taxi
6. Tempo
7. Microbus
8. Minibus
9. Bus
10. Car
11. Jeep
12. Pick Up
13. Truck (<3.5t)
14. Heavy Truck
15. Artic. Truck
16. OilTanker
17. Tractor
18. Animal Drawn
19. Other ....

42. VEHICLE MANOEUVRE
1. Left Turn
2. Right Turn
3. 'U' Turn
4. Crossing Road
5. Overtaking
6. Going Ahead
7. Reversing
8. Sudden Start
9. Sudden Stop
10. Parked
11. Other ....

43. VEHICLE LOADING
1. Legal
2. Illegal/Unsafe

44. VEHICLE DEFECT (from MVI report)
1. None
2. Lights
3. Brakes
4. Steering
5. Tyres
6. Multiple
7. Other ....

45. VEHICLE DAMAGE (Sustained in accident)
1. None
2. Front
3. Rear
4. Right
5. Left
6. Roof
7. Multiple
8. Other ....

DRIVER 2

NAME

ADDRESS

DRIVING LICENSE: 46. DISTRICT 47. NUMBER

LICENSE TYPE + CATEGORY EXPIRY DATE

48. DRIVER SEX
1. Male
2. Female

49. DRIVER INJURY
F. Fatal
G. Grievous
S. Simple Injury
N. Not Injured

50. DRIVER AGE

51. ALCOHOL
1. Alcohol Suspected
2. Not Suspected

52. SEAT BELT/HELMET
1. Seat Belt/Helmet Worn
2. Not Worn

PASSENGER CASUALTIES

Complete 1 FULL line for each passenger casualty * = See Reference boxes below

NAME AND ADDRESS	53. VEH. NO	54. SEX	55. AGE	56. * INJURY	57. * POSITION	58. * ACTION
1						
2						
3						
4.						
5						
6.						

PEDESTRIAN CASUALTIES

Complete 1 FULL line for each pedestrian casualty * = See Reference boxes below

NAME AND ADDRESS	59. VEH. NO	60. SEX	61. AGE	62. * INJURY	63. * LOCATION	64. * ACTION
1.						
2						
3.						

FOR REFERENCE ONLY

DO NOT CIRCLE

56. PASSENGER INJURY / 62. PEDESTRIAN INJURY
F. Fatal
G. Grievous Injury
S. Simple Injury

57. PASSENGER POSITION
1. Inside Vehicle
2. Outside Vehicle
3. On Roof

58. PASSENGER ACTION
1. No action
2. Boarding
3. De-boarding
4. Falling off
5. Other

63. PEDESTRIAN LOCATION
1. On pedestrian crossing
2. Within 50m of ped.crossing
3. Central Island/divider
4. Road centre
5. Footpath
6. Road side
7. Bus stop

64. PEDESTRIAN ACTION
1. No action
2. Crossing the road
3. Walking along the road
4. Walking along road side
5. Playing on the road

CONTRIBUTORY FACTORS
1. Speeding
2. Careless driving
3. Driver fatigue
4. Driving too close
5. Bad driver signals
6. Bad overtaking
7. Bad turning
8. Drunk driver
9. Pedestrian action
10. Passenger action
11. Road condition
12. Road Feature
13. Weather
14. Vehicle Defect
15. Unsafe Loading
16. Tyre Burst
17. Animal Action
18. Other ....

65.
66.
67.

Anx.3: Instructions for Filling up Accident Research Form (1/20)

সড়ক দুর্ঘটনার রিপোর্ট ফরম পুরণের নির্দেশিকা

দ্বিতীয় সংস্করণ, জানুয়ারী ২০১০

দুর্ঘটনা রিসার্চ ইন্সটিটিউট (ARI)

বাংলাদেশ প্রকৌশল বিশ্ববিদ্যালয় (BUET)

ঢাকা-১০০০

Anx.3: Instructions for Filling up Accident Research Form (2/20)

ভূমিকা

বাংলাদেশ পুলিশের নতুন সড়ক দুর্ঘটনার রিপোর্ট ফরম যথাযথভাবে পুরণের সুবিধার্থে এই নির্দেশিকা প্রকাশ করা হলো। এই পুস্তিকার শেষে একটি পূরণকৃত দুর্ঘটনার রিপোর্ট ফরম দেয়া হলো।

সড়ক দুর্ঘটনার রিপোর্ট ফরমটিতে দুই পৃষ্ঠায় তথ্য লিখার জন্য সর্বমোট ৬৭টি ঘর আছে। এই ঘরসমূহ পুরণের সময় প্রায় ক্ষেত্রেই প্রযোজ্য উত্তরে শুধু গোলদাগ দিতে হবে। অনুসন্ধানকারী অফিসার (Investigating Officer) ফরমটির সম্পূর্ণ অংশ পড়ে, প্রতিটি ঘর ক্রমানুযায়ী যথাযথভাবে পূরণ করবে।

থানা থেকে পূরণকৃত ফরমের অনুলিপি রির্পোটকারী থানায় সংরক্ষণ করতে হবে। মূল ফরমটি পুলিশ সুপার অফিসে পাঠাতে হবে। পুলিশ সুপারগণ পূরণকৃত ফরমসমূহ সংশ্লিষ্ট রেঞ্জ এর এক্সিডেন্ট ডাটা ইউনিটে (ADU) পাঠাবেন। মেট্রোপলিটন এলাকায় থানা থেকে পূরণকৃত ফরম সরাসরি মেট্রোপলিটন পুলিশ কমিশনারের অফিসে অবস্থিত এক্সিডেন্ট ডাটা ইউনিটে (ADU) পাঠাবেন। প্রত্যেক ডিআইজি/মেট্রোপলিটন পুলিশ কমিশনারের অফিসে অবস্থিত এক্সিডেন্ট ডাটা ইউনিট (ADU) দুর্ঘটনার ফরমগুলো থেকে ডাটা MAAP5 Software-এর মাধ্যমে কম্পিউটারে এন্ট্রি করবে। ডিআইজি/মেট্রোপলিটন পুলিশ কমিশনারের দপ্তর থেকে এন্ট্রিকৃত Database CD/Pendrive/E-mail-এর মাধ্যমে ঢাকাস্থ পুলিশ সদর দপ্তরে পাঠাবে। পুলিশ সদর দপ্তর হতে এন্ট্রিকৃত Database CD/Pendrive-এর মাধ্যমে রোড সেফটি সেলে পাঠাতে হবে। রোড সেফটি সেল, জাতীয় সড়ক নিরাপত্তা কাউন্সিলের দায়িত্ব পালনের অংশ হিসাবে তথ্যগুলো সংগ্রহ, বিশ্লেষণ এবং বার্ষিক রিপোর্ট তৈরী করে থাকে এবং এরপর তা' বিভিন্ন সংস্থায় পাঠানো হয়। সড়ক দুর্ঘটনার তথ্য সরকারের নীতি নির্ধারণসহ বিভিন্ন সংস্থার প্রয়োজনে এবং সড়ক দুর্ঘটনা রোধ করার লক্ষ্যে বিভিন্ন গবেষণা প্রতিষ্ঠানের প্রয়োজনে সরবরাহ করা হয়।

অসম্পূর্ণ ও ভুলভাবে পূরণকৃত ফরম সম্পূর্ণ ও শুদ্ধভাবে পূরণ করার জন্য সংশ্লিষ্ট থানায়/অনুসন্ধানকারী কর্মকর্তার নিকট ফেরত পাঠাতে হবে। রিপোর্টকারী থানা তদন্ত নথির জন্য আরও বিস্তারিত মানচিত্র, মৃত্যুর পরবর্তী রিপোর্ট, গাড়ীর পরিদর্শণ রিপোর্ট ইত্যাদির প্রয়োজন হ'তে পারে, তবে এগুলি রিপোর্টকারী থানায় রেখে দিতে হবে।

ফরমটির যেসব ঘরের প্রথমে নম্বর যুক্ত আছে (১ হইতে ৬৭ পর্যন্ত) ঐগুলি কম্পিউটারে সংরক্ষিত হবে। তা' ছাড়াও দুর্ঘটনার লিখিত বিবরণ ও দুর্ঘটনার স্থান কম্পিউটারে সংরক্ষিত থাকবে।

এই রিপোর্ট ফরমটি অনুসন্ধানকারী অফিসার কর্তৃক দুর্ঘটনার স্থানেই অথবা যত তাড়াতাড়ি সম্ভব পূরণ করতে হবে।

Anx.3: Instructions for Filling up Accident Research Form (3/20)

(ডঃ মোঃ সামছুল হক)
পরিচালক
দুর্ঘটনা রিসার্চ ইন্সটিটিউট ও
অধ্যাপক, পুরকৌশল বিভাগ
বাংলাদেশ প্রকৌশল বিশ্ববিদ্যালয়

(কিউ.এ.এস.এম.জাকারিয়া ইসলাম)
ডাটা বেইজ স্পেশালিষ্ট
দুর্ঘটনা রিসার্চ ইন্সটিটিউট
বাংলাদেশ প্রকৌশল বিশ্ববিদ্যালয়

তারিখ : জানুয়ারী ২০১০

বি.দ্র. যেসব মেট্রোপলিটন এলাকায় এক্সিডেন্ট ডাটা ইউনিট স্থাপিত হয়নি, সেসব এলাকায় রেঞ্জ অফিসে স্থাপিত ইউনিটই ডাটা এন্ট্রির কাজ করবে।

Anx.3: Instructions for Filling up Accident Research Form (4/20)

সড়ক দুর্ঘটনার রিপোর্ট ফরম পূরণ করার পদ্ধতি

(১) দুর্ঘটনার বিস্তারিত বিবরণ ঃ

1| দুর্ঘটনার রিপোর্ট নম্বর ঃ দুর্ঘটনার রিপোর্ট নম্বর রিপোর্টকারী থানা বা আঞ্চলিক হেড কোয়ার্টার কর্তৃক দেয় রিপোর্টের ক্রমিক নম্বর। প্রত্যেক থানা বা আঞ্চলিক অফিস প্রতি বৎসর ০০০১ হতে শুরু করে এই ক্রমিক নম্বর দিবে। প্রতিটি থানা একটি করে সড়ক দুর্ঘটনার হিসাব বই রাখবে যাতে দুর্ঘটনার সময়ানুক্রম পাওয়া যায় ও হেড কোয়ার্টারে ফেরত না দেয়া রিপোর্টের হদিস পাওয়া যায়। এই প্রশিক্ষণ ম্যানুয়েলের শেষে একটি হিসাব বই-এর নমুনা দেয়া হলো। এই দুর্ঘটনার রিপোর্ট নম্বরের সাথে এফ.আই.আর বা এম.সি.আর নম্বর গুলিয়ে ফেলা যাবে না।

2| প্রাথমিক তথ্য বিবরণী নম্বর ঃ থানা কর্তৃক কেস প্রতি দেয়া প্রাথমিক তথ্য বিবরণী (FIR) নম্বর।

3| থানা ঃ দুর্ঘটনার রিপোর্টকারী থানা/পুলিশ ষ্টেশন সমূহের নামের তালিকা প্রতিটি জেলা ও মেট্রোপলিটন পুলিশ বাহিনীতে রক্ষিত আছে।

4| জেলা/মেট্রোপলিটন ঃ পুলিশ জেলা বা মেট্রোপলিটন পুলিশ বাহিনীর নাম।

5| দুর্ঘটনা কবলিত গাড়ির সংখ্যা ঃ দুর্ঘটনা কবলিত সর্বমোট গাড়ির সংখ্যা। এর প্রতিটি গাড়ির জন্য অত্র ফরমের সম্পৃক্ত যানবাহন/চালক অংশ পূরণ করতে হবে।

6| হতাহত চালকের সংখ্যা ঃ দুর্ঘটনায় নিহত বা আহত চালকের মোট সংখ্যা।

7| হতাহত যাত্রীর সংখ্যা ঃ দুর্ঘটনায় নিহত বা আহত যাত্রীর মোট সংখ্যা। এর প্রতি যাত্রীর জন্য অত্র ফরমের সম্পৃক্ত যাত্রীর লাইন/অংশ পূরণ করতে হবে।

Anx.3: Instructions for Filling up Accident Research Form (5/20)

8| হতাহত পথচারীর সংখ্যা ঃ দুর্ঘটনায় নিহত বা আহত পথচারীর মোট সংখ্যা। এর প্রতি পথচারীর জন্য অত্র ফরমের সম্পৃক্ত যাত্রীর লাইন/অংশ পূরণ করতে হবে।

9| দুর্ঘটনার মাত্রা ঃ F = মৃত্যুঘটিত দুর্ঘটনা। যেখানে দুর্ঘটনার ৩০ দিনের মধ্যে কোন ব্যক্তি মৃত্যুবরণ করে। G = মারাত্মক ক্ষতজনিত দুর্ঘটনা। যেখানে দুর্ঘটনায় কোন ব্যক্তি মারাত্মকভাবে আহত হয়, তবে কেউ মৃত্যুবরণ করে না। S = সাধারণ ক্ষতজনিত দুর্ঘটনা। যেখানে কোন ব্যক্তি সাধারণভাবে আহত হয়। তবে কেউ মৃত বা মারাত্মকভাবে আহত হয় না। M = মোটর দুর্ঘটনা। যেখানে দুর্ঘটনায় কেউ হতাহত হয় না, কিন্তু গাড়ি বা সম্পদের ক্ষতি সাধিত হয়।

দুর্ঘটনার মাত্রা হতাহতের সংখ্যার উপর নির্ভর করে না বরং হতাহতদের মধ্যে সর্বোচ্চ আঘাতের মাত্রার উপর নির্ভরশীল। যেমন, কোন দুর্ঘটনায় যদি ২০ জন লোক সাধারণভাবে আহত (S) হয় ও ১ জন মারাত্মকভাবে আহত (G) হয় তবে দুর্ঘটনার মাত্রা মারাত্মক ক্ষতজনিত দুর্ঘটনা ধরতে হবে।

10| দিন ঃ সপ্তাহের যে দিন/বারে (সোম,মঙ্গল,বুধ -----) দুর্ঘটনা সংঘটিত হয়।

দুর্ঘটনার তারিখ ঃ

11| তারিখ ঃ মাসের যে তারিখে দুর্ঘটনা সংঘটিত হয়।

12| মাস ঃ যে মাসে দুর্ঘটনা সংঘটিত হয়।

13| বৎসর ঃ যে বৎসর দুর্ঘটনা সংঘটিত হয়।

14| দুর্ঘটনার সময় ঃ দুর্ঘটনা যে সময় সংঘটিত হয়। ২৪ ঘন্টার দিনকে ব্যবহার করতে হবে। উদাহরণ স্বরূপঃ সকাল ৯টা = ০৯.০০, রাত্র ৯টা = ২১.০০। তবে **এ পদ্ধতিতে যদি কোন দুর্ঘটনা রাত ঠিক ১২:০০টায় সংঘটিত হয় তবে**

Anx.3: Instructions for Filling up Accident Research Form (6/20)

দুর্ঘটনার সময় ০০:০০ বা ২৪:০০ না লিখে ০০:০১ লিখতে হবে।

রিপোর্ট করার তারিখ ঃ পুলিশের নিকট দুর্ঘটনার রিপোর্ট (FIR) করার দিন, মাস ও বৎসর।
রিপোর্ট করার সময় ঃ পুলিশের নিকট দুর্ঘটনার রিপোর্ট করার সময়।

15| সংযোগ স্থলের ধরণ ঃ দুর্ঘটনার স্থানের ধরণ বুঝে যথাযথ নম্বরে গোল দাগ দিতে হবে। যদি দুর্ঘটনাটি কোন রাস্তার সংযোগস্থলে সংঘটিত হয় তবে এই ফরমের দুর্ঘটনার অবস্থান অংশে দ্বিতীয় সড়কের নাম লিখতে হবে। এছাড়া সংঘর্ষের রেখা চিত্রের ঘরে রাস্তার সংযোগস্থলের যে রেখাচিত্র আঁকা হবে তা এই ঘরের রাস্তার সংযোগ স্থলের ধরনের সাথে অবশ্যই মিল থাকতে হবে।

উল্লেখ্য, দুর্ঘটনাটি সংযোগ স্থলের ২০ মিটারের মধ্যে সংঘটিত হয়ে থাকলে তা' সংযোগ স্থলে হয়েছে ধরে চিহ্নিত করতে হবে।

16| ট্রাফিক নিয়ন্ত্রণ ব্যবস্থা ঃ দুর্ঘটনার স্থানে অবস্থিত যানবাহন নিয়ন্ত্রণ ব্যবস্থার সাথে মিল রেখে যথাযথ ঘরে গোল দাগ দিতে হবে।

17| সংঘর্ষের ধরণ ঃ দুর্ঘটনার সংঘর্ষের ধরণ বুঝে যথাযথ চিহ্নে গোল দাগ দিতে হবে। সংঘর্ষের রেখাচিত্রে এই ঘরের সংঘর্ষের ধরনের দাগের সাথে মিল থাকতে হবে। এটা মনে রাখতে হবে যে, মুখোমুখি, পশ্চাদভাগে, সমকোন ও পার্শ্ব ঘর্ষণ জাতীয় সংঘর্ষের জন্য অন্ততঃ দুটি গাড়ি জড়িত থাকবে। একটি মাত্র গাড়ি কোন বস্তু বা পথচারীকে আঘাত করলে অথবা রাস্তার উপর উল্টে গেলে বা পাশে খাদে পড়ে গেলে এ চারটি ধরণ ব্যবহৃত হবে না।

মুখোমুখি ঃ যখন দু'টি গাড়ি মুখোমুখি সংঘর্ষে নিপতিত হয়।
পশ্চাদভাগঃ যখন একটি গাড়ি আরেকটি গাড়ির পশ্চাদভাগে আঘাত করে।

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সমকোন ঃ যখন একটি গাড়ি অন্য গাড়ির পার্শ্বে প্রায় ৯০ ডিগ্রী কোণাকুনি আঘাত করে।

পার্শ্ব ঘর্ষণ ঃ যখন দুটি গাড়ি পরস্পরের পার্শ্ব ঘর্ষণে লিপ্ত হয়। গাড়ি দুটি একই দিকে বা বিপরীত দিকে গতিশীল থাকতে হবে।

18| গাড়ী চলাচলের দিক ঃ দুর্ঘটনাস্থলের রাস্তায় গাড়ি চলাচলের দিক নির্দেশের যথাযথ ঘরে গোল দাগ দিতে হবে।

একমুখি রাস্তা ঃ যখন রাস্তায় গাড়ি শুধু একদিকে চলাচল করে।

উভয়মুখি রাস্তা ঃ যখন রাস্তায় গাড়ি শুধু উভয়দিকেই চলাচল করে।

19| রোড ডিভাইডার ঃ দুর্ঘটনাস্থলের রাস্তার অবস্থা দেখে যথাযথ ঘরে গোল দাগ দিতে হবে।

আছেঃ রাস্তার মাঝ বরাবর কম উচ্চতার দেয়াল (সড়ক দ্বীপ) থাকলে এবং গাড়ি বিপরীত দিকে যেতে না পারলে।

নাই ঃ উপরের অবস্থার বিপরীত।

20| আবহাওয়া ঃ দুর্ঘটনার সময় আবহাওয়ার অবস্থা দেখে যথাযথ ঘরে গোল দাগ দিতে হবে।

21| আলো ঃ দুর্ঘটনার সময় আলোর অবস্থা দেখে যথাযথ ঘরে গোল দাগ দিতে হবে।

22| রাস্তার জ্যামিতিক বিবরণ ঃ দুর্ঘটনার সময় রাস্তার বাস্তব অবস্থা দেখে যথাযথ ঘরে গোল দাগ দিতে হবে।

চুড়া ঃ এটা পাহাড়ের সর্বোচ্চ অবস্থানকে বোঝায় যেখানে উভয় দিক থেকে আগত গাড়িগুলির দৃষ্টিসীমা কমে যায় অর্থাৎ ড্রাইভার সামনে বেশি দুর দেখতে পায়না।

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23| রাস্তার উপরিভাগের অবস্থা ঃ দুর্ঘটনাস্থলের রাস্তার উপরিভাগের অবস্থা দেখে যথাযথ ঘরে গোলদাগ দিতে হবে।

24| রাস্তার প্রকারভেদ ঃ দুর্ঘটনা স্থলের রাস্তার উপরিভাগের প্রকারভেদ দেখে যথাযথ ঘরে গোলদাগ দিতে হবে।

25| রাস্তার প্রকৃতি ঃ দুর্ঘটনা স্থলের রাস্তার গুণাগুণ বিচার করে যথাযথ ঘরে গোলদাগ দিতে হবে।

26| রাস্তার শ্রেণী ঃ দুর্ঘটনা স্থলের রাস্তার শ্রেণী বিন্যাস নির্দেশক ঘরে গোলদাগ দিতে হবে। গুরুত্ব নির্বিশেষে প্রধান প্রধান শহরের সকল রাস্তাকে সিটি রোড হিসাবে দেখাতে হবে।

27| রাস্তার বৈশিষ্ট্য ঃ দুর্ঘটনাস্থলের রাস্তার বিশেষ বৈশিষ্ট্য নির্দেশক ঘরে গোলদাগ দিতে হবে।

সাধারণ রাস্তা ঃ যাতে বিশেষ কোন বৈশিষ্ট্য নেই।

সেতু ঃ দুর্ঘটনাটি যদি সেতুর উপর অথবা তার ২০ মিটারের মধ্যে সংঘটিত হয়ে থাকে তবে এই ঘরে গোলদাগ দিতে হবে। দাগের উপর সেতুর / নদীর নাম লিখতে হবে।

কালভার্ট ঃ দুর্ঘটনাটি যদি কোন কালভার্টের উপর অথবা কালভার্টের কারণে হয়ে থাকে তবে এই ঘরে গোলদাগ দিতে হবে।

সংকীর্ণ/বাধাপ্রাপ্ত ঃ দুর্ঘটনা স্থলে যদি কোন অস্থায়ী কারনের (যেমন হাট বাজার/গাড়ী থামানো/রাস্তা মেরামত কাজ ইত্যাদি) জন্য রাস্তা সংকীর্ণ হয়ে গাড়ী চলাচলে বাধাগ্রস্থ হয় তবে এই ঘরে গোলদাগ দিতে হবে।

28| এলাকার ধরণ ঃ দুর্ঘটনাস্থলের ধরণ বিবেচনা করে যথাযথ ঘরে গোল দাগ দিতে হবে।

শহর এলাকা ঃ যেখানে দুর্ঘটনাটি শহর বা নগরের মত বসতিপূর্ণ এলাকায় সংঘটিত হয়ে থাকে। যদি জায়গাটি শহরের সীমানার বাইরেও হয় তবুও বর্ণনাকারী অফিসার তা' শহর এলাকা বিবেচনা করতে পারেন যদি রাস্তার পার্শ্বে জনবসতি থাকে।

গ্রাম এলাকা ঃ যেখানে দুর্ঘটনাটি বসতিপূর্ণ এলাকার বাইরে সংঘটিত হয়ে থাকে। এর মধ্যে রাস্তাটি বন, আবাদী জমি বা ছোট গ্রামের মধ্য দিয়ে যেতে পারে।

(২) দুর্ঘটনার অবস্থানের তথ্য ঃ

দুর্ঘটনার উপযুক্ত অনুসন্ধান করতে হলে দুর্ঘটনা স্থলের অবস্থান-বৈশিষ্ট্য লিখতে হবে। এটা খুবই প্রয়োজনীয়, এই অংশে দুর্ঘটনাস্থলের বিস্তারিত তথ্যটি লিপিবদ্ধ করবেন, যাতে ভবিষ্যতে যে কেউ ঘটনাস্থল খুঁজে বের করতে পারেন। শুধুমাত্র অফিস ব্যবহারের জন্য ৯টি ঘর আছে। এগুলো কম্পিউটারে বিশ্লেষণের জন্য দুর্ঘটনার অবস্থানের বৈশিষ্ট্যসমূহ কোডভুক্ত করা হবে। এই ঘরগুলো পূরণ করা এই অংশের বিস্তারিত তথ্যাদির উপর নির্ভরশীল। অনেক জায়গায় কোন রাস্তা বা বস্তু বা বসতি থেকে দূরত্ব লিখতে হয়। এই দূরত্ব কিলোমিটার বা মিটারে লিখতে হবে। দূরত্ব লিখতে অপ্রয়োজনীয় কিঃ মিঃ অথবা মিঃ কেটে (অর্থাৎ প্রয়োজনীয় মিঃ অথবা কিঃ মিঃ রেখে) লিখতে হবে।

নগর/শহর/গ্রামের নাম ঃ এই ঘরে দুর্ঘটনা স্থলের নগর, শহর বা গ্রামের নাম লিখতে হবে। বসতি কেন্দ্র থেকে এর দূরত্ব লিখতে হবে। দুরত্ব শূণ্য হতে পারে, তখন ঐ ঘরে শূণ্য (০) লিখতে হবে। যদি দুর্ঘটনাস্থল বসতি থেকে অনেক দূর হয়, তা'হলে সবচেয়ে কাছের নগর/শহর/গ্রমের নাম লিখতে হবে। এই বসতি থেকে দূরত্ব ফরমের ঘরে লিখতে হবে।

দুর্ঘটনার অবস্থান ঃ

রাস্তার নাম ঃ এখানে দুর্ঘটনাস্থলের রাস্তার নাম লিখতে হবে। ন্যাশনাল রাস্তা হলে দুই প্রান্তের নগর/শহরের নামসহ একটি আদর্শ নাম

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পদ্ধতি ব্যবহার করতে হবে অথবা সড়ক ও জনপথ দপ্তর কর্তৃক ব্যবহৃত সড়ক নম্বর ব্যবহার করতে হবে।

দৃষ্ট বস্তু-১ ঃ এখানে দুর্ঘটনাস্থলের রাস্তার উপর কোন লক্ষণীয় বস্তু / স্থায়ী স্থাপনা যেমন- কিলোমিটার পোষ্ট, সেতু, স্কুল, মাদ্রাসা, মসজিদ, রাস্তার সংযোগ স্থল ইত্যাদির নাম লিখতে হবে। এই লক্ষণীয় বস্তুর/স্থাপনার অবস্থানের দূরত্ব ফরমে জায়গামত লিখতে হবে।

দৃষ্ট বস্তু-২ ঃ এখানে দৃষ্ট বস্তু-১ এর বিপরীত দিকের রাস্তায় অবস্থিত কোন লক্ষণীয় বস্তু / স্থায়ী স্থাপনা যেমন- কিলোমিটার পোষ্ট, সেতু, স্কুল, মাদ্রাসা, মসজিদ, রাস্তার সংযোগ স্থল ইত্যাদির নাম লিখতে হবে। দুর্ঘটনার স্থান থেকে ঐ লক্ষণীয় বস্তুর দূরত্ব ফরমে জায়গামত লিখতে হবে।

শুধুমাত্র সংযোগ স্থানের দুর্ঘটনা ঃ রাস্তার সংযোগ স্থলের দুর্ঘটনার ক্ষেত্রে দুইটি রাস্তারই নাম লিখতে হবে। দুর্ঘটনার স্থান থেকে এই সংযোগ স্থলের দূরত্ব ফরমে জায়গামত লিখতে হবে। দুর্ঘটনাটি যদি এই রাস্তা দুইটির ঠিক সংযোগ স্থলে হয়ে থাকে তবে দূরত্ব শূণ্য লিখতে হবে।

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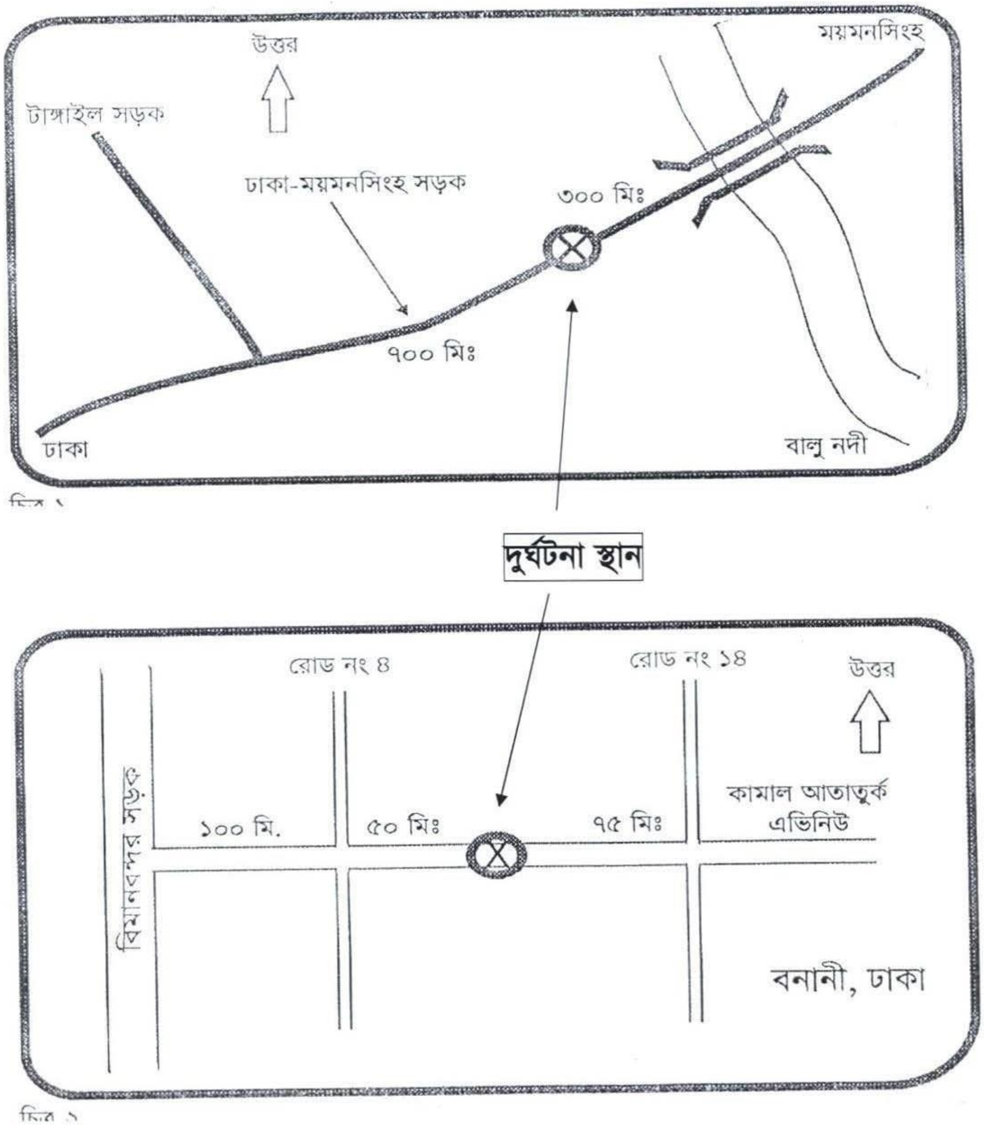
দুর্ঘটনাস্থলের রেখা চিত্র ঃ এই চিত্র অত্যন্ত দরকারী, যাতে ভবিষ্যতে যে কেউই চিত্র দেখে দুর্ঘটনার স্থানটি চিহ্নিত করতে পারে। এখানে শুধুমাত্র রাস্তাটির (বা রাস্তাগুলোর) রেখা চিত্র আঁকলেই চলবে এবং আশে-পাশের দৃষ্ট স্থাপনা সমূহ থেকে দুর্ঘটনার স্থানটির দূরত্ব দেখাতে হবে। মনে রাখতে হবে যে, এই রেখা চিত্রটি শুধুমাত্র দুর্ঘটনাস্থলের অবস্থান জানতে ব্যবহৃত হবে, কাজেই এতে দুর্ঘটনার ধরণের খুঁটিনাটি দেখানোর প্রয়োজন নেই। সংঘর্ষের ধরণের বিবরণ পরে বর্ণিত সংঘর্ষের রেখাচিত্রে দিতে হবে। নিম্নে দুইটি দুর্ঘটনাস্থলের রেখা চিত্রের নমুনা দেয়া হলো।



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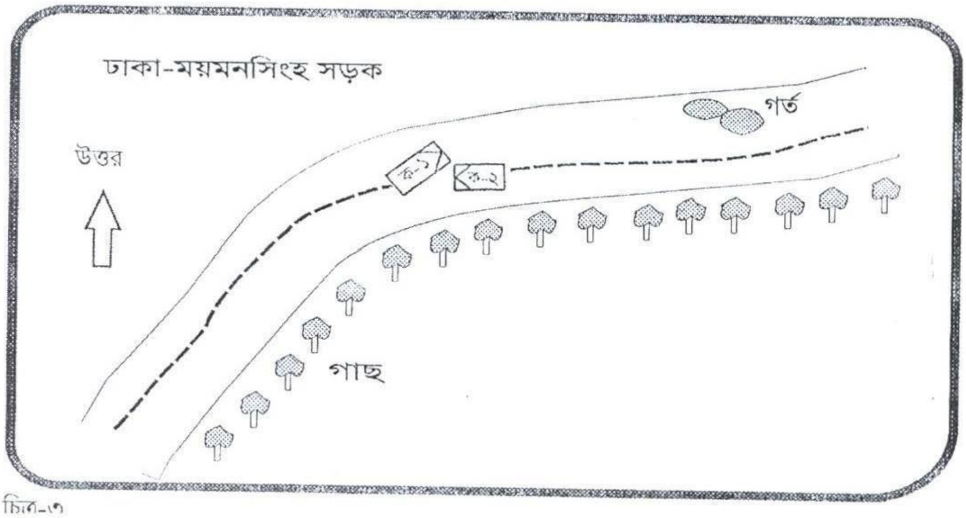
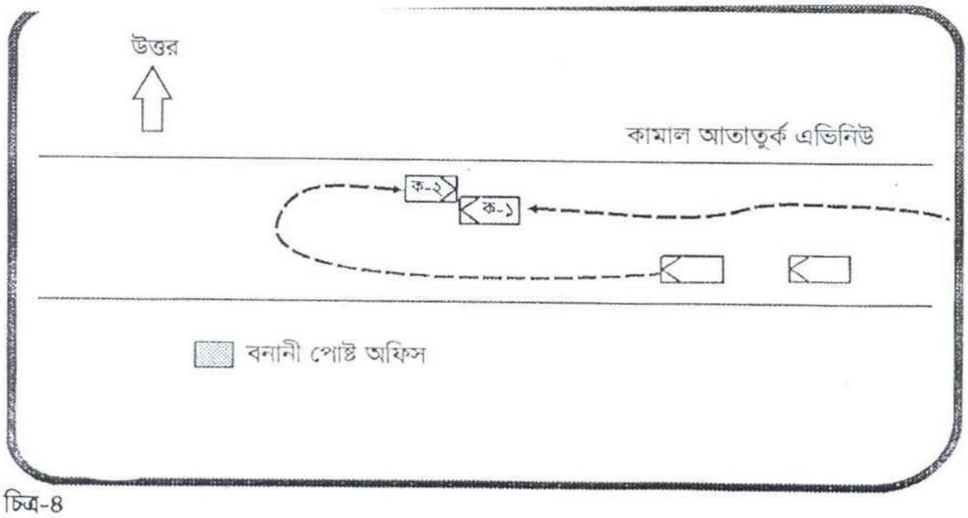
সংঘর্ষের রেখা চিত্র ঃ এই রেখাচিত্রটি দুর্ঘটনা তদন্তকারীদের জন্য খুবই গুরুত্বপূর্ণ এবং বহু বৎসর পরও তালিকাভুক্ত দুর্ঘটনা-প্রবণ স্থানসমূহের বিশ্লেষণের জন্য প্রয়োজন হয়। এটা একটি সংঘর্ষের রেখা চিত্র মাত্র, আগে বর্ণিত দুর্ঘটনা স্থলের চিত্র নয়। এখানে দুর্ঘটনায় জড়িত প্রত্যেকটি গাড়ির ও পথচারীর রাস্তার উপর অবস্থানস্থল ও চলাচলের পথ দেখাতে হবে। দুর্ঘটনার আগে প্রত্যেকটি গাড়ির গমনপথ ভাঙ্গা দাগ দিয়ে দেখাতে হবে। সংঘর্ষের সময় গাড়িগুলি যে যে দিকে যাচ্ছিল, তা' তীর চিহ্ন দিয়ে দেখাতে হবে। দুর্ঘটনাস্থলের রাস্তার অবস্থানের বিস্তারিত তথ্যাদি সংরক্ষণ করতে হবে। গাড়িগুলোকে ক-১, ক-২ ইত্যাদি প্রতীকে দেখাতে হবে। নিম্নে কয়েকটি সংঘর্ষের রেখাচিত্রের নমুনা দেয়া হল।



চিত্র-৩

Anx.3: Instructions for Filling up Accident Research Form (13/20)



চিত্র-৪

(৩) পুলিশের কার্যাদি ঃ

দুর্ঘটনার সংক্ষিপ্ত বিবরণ ঃ এখানে দুর্ঘটনার স্পষ্ট/সঠিক বিবরণ দিতে হবে। গাড়িগুলোকে ক-১, ক-২ ইত্যাদি বলে উল্লেখ করতে হবে। এখানে গাড়ি, পথযাত্রী বা অন্য কিছু, যা দুর্ঘটনার জন্য দায়ী সবই উল্লেখ করতে হবে।

সাক্ষী ঃ এখানে দু'জন সাক্ষীর নাম ও ঠিকানা লিখতে হবে।

বিবরণ লিপিবদ্ধকারী অফিসার ঃ এখানে দুর্ঘটনার বিবরণ লিপিবদ্ধকারী অফিসারের নাম ও পদবী লিখতে হবে।

অনুসন্ধানকারী অফিসার ঃ এখানে দুর্ঘটনার রিপোর্ট ফরম পূরণকারী ও অনুসন্ধানকারী অফিসারের নাম ও পদবী লিখতে হবে।

তত্ত্বাবধানকারী অফিসার ঃ এখানে দুর্ঘটনার রিপোর্ট ফরম পরীক্ষাকারী ও এর সম্পূর্ণতা ও নির্ভুলতা সম্পর্কে অনুমোদনকারী তত্ত্বাবধায়ক অফিসারের নাম ও পদবী লিখতে হবে।

আইনের ধারা ঃ এখানে সড়ক দুর্ঘটনার সংশ্লিষ্ট আইনের ধারা উল্লেখ করতে হবে।

Anx.3: Instructions for Filling up Accident Research Form (14/20)

কেসের অবস্থা ঃ তিনটি উল্লেখিত অবস্থার নির্দিষ্ট একটিতে গোল চিহ্ন দিতে হবে।

(৪) যানবাহন/চালক এর বিস্তারিত তথ্য ঃ

দুর্ঘটনা কবলিত প্রতিটি যানবাহনের জন্য এই যানবাহন/চালক অংশ পূরণ করতে হবে। দুর্ঘটনায় ২টির অধিক যানবাহন জড়িত থাকলে অতিরিক্ত ফরম পূরণ করতে হবে ও মূল ফরমের সাথে গেঁথে দিতে হবে। অতিরিক্ত ফরম ব্যবহৃত হলে তাতে দুর্ঘটনার ক্রমিক নং, থানা, জেলা/মেট্রোপুলিশ ও সন লিখতে হবে যাতে তা' সনাক্ত করা যায়। অতিরিক্ত ফরম ব্যবহৃত হলে সবগুলো একসাথে গেঁথে দিতে হবে।

৪.১ যানবাহন এর বিস্তারিত তথ্য ঃ

মালিকের নাম ঃ যানবাহনের মালিকের নাম লিখতে হবে।

মালিকের ঠিকানা ঃ যানবাহনের মালিকের যোগাযোগের ঠিকানা লিখতে হবে।

যানবাহনের প্রস্তুতকারী + তৈরি সন ঃ গাড়িটির বিস্তারিত বিবরণ যথা প্রস্তুতকারী, গঠন প্রকৃতি ও তৈরির সন লিখতে হবে।

38| জেলা ঃ যে জেলায় গাড়িটি রেজিস্ট্রেশন করা হয়েছে। অর্থাৎ ঢাকা, চট্টগ্রাম ইত্যাদি লিখতে হবে।

39| নম্বর ঃ এখানে গাড়িটির কেবলমাত্র রেজিস্ট্রেশন নম্বর লিখতে হবে। এতে গাড়িটির ধরণের সহিত মিল থাকতে হবে।

40| বৈধ ফিটনেস সার্টিফিকেট ঃ প্রযোজ্য ঘরে গোলদাগ দিতে হবে।

আছে ঃ গাড়িটির বৈধ ফিটনেস সার্টিফিকেট আছে।

নাই ঃ গাড়িটির বৈধ বা কোন রকম ফিটনেস সার্টিফিকেট নেই।

প্রযোজ্য নয় ঃ এই ধরণের গাড়ির জন্য ফিটনেস সার্টিফিকেটের প্রয়োজন নেই। (যেমন যন্ত্রবিহীন

Anx.3: Instructions for Filling up Accident Research Form (15/20)

গাড়ি এবং নসিমন/করিমন/ভটভটি এই ধরনের স্থানীয়ভাবে তৈরী গাড়ী)।

বীমাকৃত ঃ কৃত বীমার ধরণ বুঝে প্রযোজ্য ঘরে গোল দাগ দিতে হবে।

41| যানবাহনের ধরণ ঃ যানবাহনের ধরণের সাথে মিল রেখে গোল দাগ দিতে হবে। নসিমন/করিমন ধরনের যানবাহনকে অন্যান্য লেখা ঘরে পূরণ করতে হবে।

42| যানবাহন চলাচলের ধরণ ঃ দুর্ঘটনার সময় গাড়িটি যে কৌশলে চলছিল (বা চলার চেষ্টা করছিল) তার সাথে মিল রেখে যথাযথ ঘরে গোল দাগ দিতে হবে। এটা মনে রাখতে হবে যে, পার্ক অবস্থার অর্থ গাড়িটিকে দেখাশুনার কেউ নেই বা গাড়িটি সচল নয়। এতে রাস্তার ভীড়ের/জ্যামের মধ্যে দাঁড়ানো গাড়ি বা রাস্তায় সংযোগ স্থলে পারাপারের সারিবদ্ধ গাড়ি বুঝায় না।

আড়াআড়ি অতিক্রম ঃ এতে গাড়িটি অন্য একটি আড়াআড়ি বড় রাস্তা অতিক্রম করে সম্মুখে যাওয়া বুঝায়।

ওভার টেকিং ঃ যদি গাড়িটি অন্য গাড়িকে অতিক্রম করা অবস্থায় থাকে তবে তাকে অগ্রগমন না বলে ওভার টেকিং বলতে হবে।

43| যানবাহনে মালামাল বোঝাই ঃ গাড়িটিতে মালামাল বোঝাই করার ধরণ দেখে যথাযথ ঘরে গোল দাগ দিতে হবে। যদি অনুসন্ধানকারী অফিসারের মতে মালামাল বোঝাই নিরাপদ ও আইনানুগ হয় তবে প্রথম ঘর চিহ্নিত করতে হবে। কিন্তু যদি মালামাল বোঝাই বিপদজনক ও বে-আইনী হয় তবে দ্বিতীয় ঘর চিহ্নিত করতে হবে। বিপদজনক ও বে-আইনী বলতে অতিরিক্ত মালামাল বহন, ছাদে যাত্রী বহন ইত্যাদি বোঝায়।

Anx.3: Instructions for Filling up Accident Research Form (16/20)

44| যানবাহনের ত্রুটি ঃ বিআরটিএ কর্তৃক মটরযানের পরিদর্শন রিপোর্ট দাখিল করার পর এই ঘর পূরণ করতে হবে।

45| যানবাহনের ক্ষতি ঃ দুর্ঘটনার জন্য যানবাহনের যে ক্ষতি হয়েছে তার সাথে মিলিয়ে যথাস্থানে গোল দাগ দিতে হবে। দুর্ঘটনার আগে কোন ক্ষতি থাকলে তা' বিবেচনা করা যাবে না। যদি কোন ক্ষতি দেখা না যায় তা'হলে প্রথম ঘরে দাগ দিতে হবে।

4.2 চালকের বিস্তারিত তথ্য ঃ

নাম ঃ এখানে চালকের নাম লিখতে হবে।

ঠিকানা ঃ এখানে চালকের সঙ্গে যোগাযোগের ঠিকানা লিখতে হবে।

46| জেলা ঃ এখানে চালকের ড্রাইভিং লাইসেন্স যে জেলা হইতে ইস্যু করা হয়েছে তা' লিখতে হবে।

47| নম্বর ঃ এখানে চালকের ড্রাইভিং লাইসেন্স নম্বর লিখতে হবে।

লাইসেন্সের ধরণ ঃ লাইসেন্সের ধরণ ও যানবাহনের শ্রেণী লিখতে হবে।

48| চালকের লিঙ্গ ঃ চালক পুরুষ হলে "১" ও স্ত্রীলোক হলে "২" ঘরে গোল দাগ দিতে হবে।

49| চালকের বয়স ঃ এখানে চালকের বয়স বৎসরে লিখতে হবে।

50| চালকের ক্ষত ঃ নিম্নে বর্ণিত যথাযথ অক্ষরযুক্ত ঘরে গোলদাগ দিতে হবে।

F (মৃত্যু) ঃ দুর্ঘটনায় বা দুর্ঘটনার ৩০ দিনের মধ্যে যদি চালক মৃত্যুবরণ করে।

G (মারাত্মক) ঃ দুর্ঘটনায় যদি চালক মারাত্মক আঘাত প্রাপ্ত হয়।

S (সাধারণ) ঃ দুর্ঘটনায় যদি চালক সাধারণ আঘাত প্রাপ্ত হয়।

N (অক্ষত) ঃ দুর্ঘটনায় যদি চালক আঘাত প্রাপ্ত না হয়।

51| মদ্যপ অবস্থা ঃ এখানে চালক মদ্যপ বা সন্দেহ মুক্ত কিনা লিখতে হবে।

52| সীট বেল্ট/হেলমেট ঃ এখানে চালক সীট বেল্ট বাঁধা অবস্থায় ছিল কিনা এবং দ্বিচক্রযানের ক্ষেত্রে চালক হেলমেট পরিহিত ছিল কিনা লিখতে হবে।

(5) হতাহত যাত্রীর বিবরণ ঃ

দুর্ঘটনায় হতাহত প্রত্যেক যাত্রীর জন্য একটি করে লাইন পূরণ করতে হবে। অক্ষত যাত্রীকে অন্তর্ভুক্ত করা যাবে না।

যদি দুর্ঘটনায় ছয় জনের অধিক হতাহত যাত্রী থাকে তবে অতিরিক্ত ফরম পূরণ করতে হবে। যদি অতিরিক্ত ফরম ব্যবহৃত হয়, তবে তাতে দুর্ঘটনার ক্রমিক নম্বর, থানা, জেলা/মেট্রোপুলিশ ও সন উল্লেখ করতে হবে। অতিরিক্ত ফরম ব্যবহৃত হলে সবগুলো ফরম একসাথে গেঁথে দিতে হবে।

এই অংশ পূরণ করতে ফরমের পথচারীর বিবরণ অংশের পাদটিকার 'বি' নির্দেশ দেখা যেতে পারে। এতে গোল দাগ দিতে হবে না, কারণ যাত্রী সংখ্যা বেশি হতে পারে।

দুর্ঘটনায় নিহত/আহত একজন যাত্রীর জন্য এই ফরমের একটি লাইন পূরণ করতে হবে।

53| যানবাহন নম্বর ঃ যাত্রী যে যানবাহনে ভ্রমণরত ছিলেন সেই নম্বর লিখতে হবে (যেমন ১ নং যানবাহন/ ২ নং যানবাহন বা শুধুমাত্র ১,২ ইত্যাদি)। মনে রাখতে হবে যানবাহনের এই নং গাড়ির নম্বর প্লেট/রেজিষ্ট্রেশন নং না।

Anx.3: Instructions for Filling up Accident Research Form (18/20)

54| যাত্রীর লিঙ্গ ঃ যাত্রী পুরুষ হলে "১" ও স্ত্রীলোক হলে "২" লিখতে হবে।

55| যাত্রীর বয়স ঃ এখানে যাত্রীর বয়স বৎসরে লিখতে হবে।

56| যাত্রীর ক্ষত ঃ এখানে যাত্রীর ক্ষতের সাথে মিলিয়ে নিচের যে কোন একটি অক্ষর লিখতে হবে।

F (মৃত্যু) ঃ দুর্ঘটনায় বা দুর্ঘটনার ৩০ দিনের মধ্যে যদি যাত্রী মৃত্যুবরণ করে।

G (মারাত্মক) ঃ দুর্ঘটনায় যদি যাত্রী মারাত্মক আঘাত প্রাপ্ত হয়।

S (সাধারণ) ঃ দুর্ঘটনায় যদি যাত্রী সাধারণ আঘাত প্রাপ্ত হয়।

57| যাত্রীর অবস্থান ঃ এই জায়গায় যাত্রীর অবস্থানের উপর বর্ণিত নিচের ছকে দেওয়া নম্বরের সাথে মিলিয়ে শুধু একটি নম্বর লিখতে হবে। কোন নম্বরে গোল দাগ দিতে হবে না। কারণ এটা শুধু নির্দেশিকার জন্য। এখানে যাত্রীর অবস্থান "গাড়ীর বাইরে" বলতে - বাসে উঠাকালীন/বাস বা ট্রাকের ছাদে/ রিক্সা ভ্যান ধরনের উন্মুক্ত যানের আরোহীকে বোঝায়।

58| যাত্রীর কার্যক্রম ঃ এই জায়গায় যাত্রীর কার্যক্রমের উপর বর্ণিত নিচের ছকে দেওয়া নম্বরের সাথে মিলিয়ে শুধু একটি নম্বর লিখতে হবে। কোন নম্বরে গোল দাগ দিতে হবে না। কারণ এটা শুধু নির্দেশিকার জন্য। এখানে যাত্রীর কার্যক্রম বলতে - যাত্রী দুর্ঘটনার সময় কি করছিল তা বোঝায়।

(6) হতাহত পথচারীর বিবরণঃ

দুর্ঘটনায় হতাহত প্রত্যেক পথচারীর জন্য একটি করে লাইন পূরণ করতে হবে। অক্ষত পথচারীকে অন্তর্ভুক্ত করা যাবে না।

Anx.3: Instructions for Filling up Accident Research Form (19/20)

যদি দুর্ঘটনায় তিন জনের অধিক হতাহত পথচারী থাকে, তা'হলে অতিরিক্ত ফরম পূরণ করতে হবে। যদি অতিরিক্ত ফরম ব্যবহৃত হয়, তবে তাতে দুর্ঘটনার ক্রমিক নম্বর, থানা, জেলা/মেট্রো-পুলিশ ও সন উল্লেখ করতে হবে যাতে তা' সহজেই সনাক্ত করা যায়। এই অতিরিক্ত ফরমে পথচারী সংখ্যা (পথচারী ৪, পথচারী ৫...) উল্লেখ করতে হবে। অতিরিক্ত ফরম ব্যবহৃত হলে সবগুলি ফরম একসাথে গেঁথে দিতে হবে।

এই অংশ পূরণ করতে নিচের পাদটিকার 'বি' নির্দেশ দেখা যেতে পারে। এতে গোলদাগ দিতে হবে না। কারণ পথচারীর সংখ্যা বেশি হতে পারে।

দুর্ঘটনায় নিহত/আহত একজন পথচারীর জন্য এই ফরমের একটি লাইন পুরণ করতে হবে।

59| যানবাহন নম্বর ঃ যে গাড়ি দ্বারা পথচারী আঘাত প্রাপ্ত হয় সেই গাড়ি নম্বর লিখতে হবে (যেমন গাড়ি নং ক-১, ক-২ অথবা শুধু ১,২)। মনে রাখতে হবে যানবাহনের এই নং গাড়ির নম্বর প্লেট/রেজিষ্ট্রেশন নং না।

60| পথচারীর লিঙ্গ ঃ পথচারী পুরুষ হলে "১" ও স্ত্রীলোক হলে "২" লিখতে হবে।

61| পথচারীর বয়স ঃ এখানে পথচারীর বয়স বৎসরে লিখতে হবে।

62| পথচারীর ক্ষত ঃ এখানে পথচারীর ক্ষতের সাথে মিলিয়ে নিচের যে কোন একটি অক্ষর লিখতে হবে।

F (মৃত্যু) ঃ দুর্ঘটনায় বা ৩০ দিনের মধ্যে যদি পথচারী মৃত্যুবরণ করে।

G (মারাত্মক) ঃ দুর্ঘটনায় যদি পথচারী মারাত্মক আঘাত প্রাপ্ত হয়।

S (সাধারণ) ঃ দুর্ঘটনায় যদি পথচারী সাধারণ আঘাত প্রাপ্ত হয়।

Anx.3: Instructions for Filling up Accident Research Form (20/20)

63| পথচারীর অবস্থান ঃ এই জায়গায় পথচারীর অবস্থানের উপর বর্ণিত নিচের ছকে দেয়া নম্বরের সাথে মিলিয়ে শুধু একটি নম্বর লিখতে হবে। কোন নম্বরে গোল দাগ দিতে হবে না। কারণ এটা শুধু নির্দেশিকার জন্য।

64| পথচারীর কার্যক্রম ঃ এই জায়গায় পথচারীর কার্যক্রমের উপর বর্ণিত নিচের ছকে দেয়া নম্বরের সাথে মিলিয়ে শুধু একটি নম্বর লিখতে হবে। কোন নম্বরে গোল দাগ দিতে হবে না। কারণ এটা শুধু নির্দেশিকার জন্য।

(7) সম্ভাব্য সহায়ক কারণ ঃ

নিচের দেয়া তিনটি ঘরে দুর্ঘটনার সম্ভাব্য সহায়ক কারণ নির্দেশ করা যেতে পারে। এই তিনটি ঘরের ছকে দেয়া সংখ্যা সমূহ থেকে সম্ভাব্য সহায়ক কারণ নির্দেশক সংখ্যা লিখতে হবে। যদি সহায়ক কারণ তিনটির কম হয়, তবে বাকি ঘরগুলি খালি রাখতে হবে।

65| সহায়ক কারণ ১ ঃ দুর্ঘটনার জন্য গুরুত্বপূর্ণ সহায়ক কারণ নির্দেশক সংখ্যা লিখতে হবে।

66| সহায়ক কারণ ২ ঃ দুর্ঘটনার জন্য দ্বিতীয় গুরুত্বপূর্ণ সহায়ক কারণ নির্দেশক সংখ্যা লিখতে হবে। যদি দ্বিতীয় কোন সহায়ক কারণ না থাকে, তা'হলে এই ঘর খালি রেখে দিতে হবে।

67| সহায়ক কারণ ৩ ঃ দুর্ঘটনার জন্য তৃতীয় গুরুত্বপূর্ণ সহায়ক কারণ নির্দেশক সংখ্যা লিখতে হবে। যদি তৃতীয় কোন সহায়ক কারণ না থাকে, তবে এই ঘর খালি রেখে দিতে হবে।

-- সমাপ্ত --

Anx.4: Year-wise Public Bus Accident Severities (1/17)

Day of Week

Year	Accident severity	Days of Week							
		1	2	3	4	5	6	7	Total
2017	F	14	14	13	20	13	20	16	110
	G	5	3	6	3	4	2	4	27
	M	2						1	3
	S	1	1	2	1	2	2		9
2018	F	12	12	10	10	13	13	19	89
	G	4	4	6	6	2	4	5	31
	M	2	1		2				5
	S			1	1				2
2019	F	8	21	12	20	13	13	8	95
	G	6	4	6	3	5	7	5	36
	M		1						1
	S	2	3			3			8

Anx.4: Year-wise Public Bus Accident Severities (2/17)

Day of Week

2020	F	6	14	7	8	10	3	10	58
	G	3	1	2	3	4	3	3	19
	M		1						1
	S			1		1	1	1	4
	Grand Total	65	80	66	77	70	68	72	498

Notes: 1=Monday, 2=Tuesday, 3=Wednesday, 4=Thursday, 5=Friday, 6=Saturday,

7=Sunday Source: ARI Accident Database 2017-2020

Anx.4: Year-wise Public Bus Accident Severities (3/17)

Month of Year

Year	Accident severity	Months of Year												
		01	02	03	04	05	06	07	08	09	10	11	12	Total
2017	F	12	11	13	7	4	9	14	6	12	8	8	6	110
	G	3	5	2	2	2		5	1	2			5	27
	M				1	1					1			3
	S	2			1	3	1			2				9
2018	F	5	9	12	9	10	6	8	6	10	6	4	4	89
	G	2	2		4	5		4	5	4	1	2	2	31
	M					1	1	2				1		5
	S			1						1				2
2019	F	6	9	6	4	10	7	6	6	12	5	11	13	95
	G	1	2	1	6	2	2	5	5	3	2	4	3	36
	M						1							1
	S			4			1	2		1				8
2020	F	14	5	11	2	4	3	5	12	2				58
	G	7	4				1	1	3	3				19

Anx.4: Year-wise Public Bus Accident Severities (4/17)

Month of Year

	M		1											1
	S	2							2					4
	Grand Total	54	48	50	36	42	32	52	46	52	23	30	33	498

Notes: 1=January, 2=February, 3=March, 4=April, 5=May, 6=June, 7=July, 8=August, 9=September, 10=October, 11=November, 12=December Source: ARI Accident Database 2017-2020

Anx.4: Year-wise Public Bus Accident Severities (5/17)

Junction Type

Year	Accident severity	Junction Type						
		1	2	3	4	5	7	Total
2017	F	48	23	18	1	4	16	110
	G	15	3	4		1	4	27
	M	1	1	1				3
	S	4	3	1			1	9
2018	F	58	13	6		1	11	89
	G	19	6	1		3	2	31
	M	3				1	1	5
	S	1	1					2
2019	F	54	6	4	3	1	27	95
	G	18	4	3	1	1	9	36
	M	1						1
	S	4	1	3				8

Anx.4: Year-wise Public Bus Accident Severities (6/17)

Junction Type

2020	F	32	2	3	10	2	9	58
	G	11	2		2		4	19
	M						1	1
	S	2		1	1			4
	Grand Total	271	65	45	18	14	85	498

Notes: 1=Not at junction, 2=Cross junction, 3=Tee junction, 4=Staggered tee junction, 5=Roundabouts, 6= Railway/level crossing, 7=Other Source: ARI Accident Database 2017-2020

Anx.4: Year-wise Public Bus Accident Severities (7/17)

Traffic Control System

Year	Accident severity	Traffic Condition							
		1	2	3	4	5	6	8	Total
2017	F	16	10	3	55	3	8	15	110
	G	7	3		12			5	27
	M	1			1			1	3
	S	3			5			1	9
2018	F	27	4	1	48	2		7	89
	G	11	3		15	1		1	31
	M	2	1		1			1	5
	S				2				2
2019	F	15	8	1	65	1		5	95
	G	4	1		26	1	1	3	36
	M				1				1
	S	2	1		5				8

Anx.4: Year-wise Public Bus Accident Severities (8/17)

Traffic Control System

2020	F	14	6	3	32			3	58
	G	2	2		13			2	19
	M							1	1
	S				2			2	4
	Grand Total	104	39	8	283	8	9	47	498

Notes: 1=No control, 2= Centerline marking, 3=Pedestrian crossing, 4=Police controlled, 5=Traffic lights, 6=Police + Traffic lights, 7=Stop/Give way sign, 8=Other

Source: ARI Accident Database 2017-2020

Anx.4: Year-wise Public Bus Accident Severities (9/17)

Collision Type

Year	Accident severity	Collision Type										
		01	02	03	04	05	06	07	08	09	10	Total
2017	F	4	13		5	2	2	1	1	80	2	110
	G	1	7		2			1	1	15		27
	M	1	1								1	3
	S	1	1					1	1	4	1	9
2018	F	5	12		10	1				59	2	89
	G		8		1				2	18	2	31
	M		2		1		1	1				5
	S		1							1		2
2019	F	6	13		8			3	4	59	2	95
	G		11		2					22	1	36
	M		1									1
	S		2		2				3	1		8

Anx.4: Year-wise Public Bus Accident Severities (10/17)

Collision Type

2020	F	2	12		6				1	36	1	58
	G		3	1	1				1	11	2	19
	M							1				1
	S		1							3		4
	Grand Total	20	88	1	38	3	3	8	14	309	14	498

Notes:1=Head on, 2=Rear end, 3=Right angle, 4=Side swipe, 5=Overturn, 6=Hit object in road, 7=Hit object off road, 8=Hit parked vehicle, 9=Hit pedestrian, 10=Hit animal,

Source: ARI Accident Database 2017-2020

Anx.4: Year-wise Public Bus Accident Severities (11/17)

Weather Condition

Year	Accident severity	Weather Condition				
		1	2	3	4	Total
2017	F	107	1		2	110
	G	27				27
	M	3				3
	S	9				9
2018	F	88	1			89
	G	30	1			31
	M	5				5
	S	2				2
2019	F	94	1			95
	G	35	1			36
	M	1				1
	S	8				8
2020	F	55	2	1		58
	G	19				19
	M	1				1
	S	4				4
	Grand Total	488	7	1	2	498

Notes: 1=Fair, 2=Rain, 3=Wind, 4=Fog

Source: ARI Accident Database 2017-2020

Anx.4: Year-wise Public Bus Accident Severities (12/17)

Light Condition

Year	Accident severity	Light Condition				
		1	2	3	4	Total
2017	F	57	12	36	5	110
	G	17	5	3	2	27
	M	2		1		3
	S	3	2	4		9
2018	F	40	21	24	4	89
	G	17	3	11		31
	M	2	1	2		5
	S	1		1		2
2019	F	51	15	23	6	95
	G	18	4	13	1	36
	M	1				1
	S	3	3	2		8
2020	F	31	8	15	4	58
	G	11	1	6	1	19
	M			1		1
	S	3		1		4
	Grand Total	257	75	143	23	498

Notes: 1=Daylight, 2=Dawn/Dusk, 3=Night (lit), 4= Night

(unlit) Source: ARI Accident Database 2017-2020

Anx.4: Year-wise Public Bus Accident Severities (13/17)

Geometric Condition

Year	Accident severity	Road Geometry					
		1	2	3	4	5	Total
2017	F	101	5	1	2	1	110
	G	24	1	1	1		27
	M	3					3
	S	8		1			9
2018	F	83	1	4	1		89
	G	30	1				31
	M	5					5
	S	2					2
2019	F	89	3	3			95
	G	34	1		1		36
	M	1					1
	S	8					8
2020	F	54	2	1	1		58
	G	18		1			19
	M	1					1
	S	3				1	4
	Grand Total	464	14	12	6	2	498

Notes: 1=Straight + Flat, 2=Curve only, 3=Slope only, 4=Curve + Slope,

5=Crest Source: ARI Accident Database 2017-2020

Anx.4: Year-wise Public Bus Accident Severities (14/17)

Road Surface Quality

Year	Accident severity	Surface Quality			
		1	2	3	Total
2017	F	102	6	2	110
	G	26	1		27
	M	3			3
	S	8		1	9
2018	F	88	1		89
	G	29	1	1	31
	M	5			5
	S	2			2
2019	F	92	1	2	95
	G	32	2	2	36
	M	1			1
	S	6		2	8
2020	F	57		1	58
	G	16	1	2	19
	M	1			1
	S	4			4
	Grand Total	472	13	13	498

Notes: 1=Good, 2=Rough, 3=Under repair Source: ARI Accident Database 2017-2020

Anx.4: Year-wise Public Bus Accident Severities (15/17)

Road Class

Year	Accident severity	Road Class					
		1	2	3	4	5	Total
2017	F	50	3	1		56	110
	G	8	3	1		15	27
	M	2				1	3
	S	2	2			5	9
2018	F	58	3	2	2	24	89
	G	13		1		17	31
	M	2	1			2	5
	S	1				1	2
2019	F	42	4	3	1	45	95
	G	6	3			27	36
	M	1					1
	S	6	1			1	8
2020	F	33	5	2	1	17	58
	G	6	2			11	19
	M	1					1
	S					4	4
	Grand Total	231	27	10	4	226	498

Notes:; 1=National, 2=Regional, 3=Feeder, 4=Rural road, 5=City

road Source: ARI Accident Database 2017-2020

Anx.4: Year-wise Public Bus Accident Severities (16/17)

Road Class

Year	Accident severity	Road Feature					
		?	1	2	4	5	Total
2017	F		108			2	110
	G		26			1	27
	M		2			1	3
	S		9				9
2018	F		87	1		1	89
	G		31				31
	M		5				5
	S		2				2
2019	F	1	91	1	1	1	95
	G		36				36
	M		1				1
	S		8				8
2020	F		57			1	58
	G		19				19
	M					1	1
	S		4				4
	Grand Total	1	486	2	1	8	498

Notes: *"?" means blank data field; 1=None, 2=Bridge, 3=Culvert, 4=Narrowing/Restriction, 5=Speed breakers

Source: ARI Accident Database 2017-2020

Anx.4: Year-wise Public Bus Accident Severities (17/17)

Road Location

Year	Accident severity	Location Type		
		01	2	Total
2017	F	110		110
	G	26	1	27
	M	3		3
	S	9		9
2018	F	88	1	89
	G	31		31
	M	5		5
	S	2		2
2019	F	95		95
	G	36		36
	M	1		1
	S	8		8
2020	F	58		58
	G	19		19
	M	1		1
	S	4		4
	Grand Total	496	2	498

Notes: 1=Urban area, 2=Rural area

Source: ARI Accident Database 2017-2020