ASSESSING VULNERABLE ROAD USERS (VRUs) BEHAVIOR FROM SAFETY, MOBILITY AND POLICY PERSPECTIVES

BY

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Approval

The paper titled "Assessing Vulnerable Road Users (VRUs) Behavior from Safety, Mobility & Policy Perspectives" submitted by Farhan Anjum Badhon, Mohammad Raiyan Tamzid, Niaz Ahmed and Lubaena Masud has been accepted as partial attainment of the requisite for the degree, Bachelor of Science in Civil Engineering.

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Declaration

It is hereby declared that this thesis/project report, in whole or in part, has not been submitted elsewhere for the award of any Degree or Diploma.

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Dedication

To our loving family members and revered teachers

for

their guidance, forbearance, and most notably, for believing in us.

Acknowledgement

All glory be to Almighty Allah, by whose mercy we were able to complete our research agenda. Our deepest appreciation will always be directed towards Allah, the kindest and most compassionate.

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Preamble

The aim of this study was to evaluate the behavior of Vulnerable Road Users (VRUs) from a safety & mobility aspect. Additionally, it recommends relevant policies for enhancing the safety of VRUs. In this study, Vulnerable Road Users (VRUs) comprise pedestrians, bicyclists, NMVs, and motorcyclists. The research is titled "Assessing Vulnerable Road Users (VRUs) Behavior from Safety, Mobility & Policy Perspectives". The research's final goal was achieved by integrating four independent objectives that targeted the four VRU groups described earlier. The objectives are, i) Analyzing the risk perceptions of vehicle-to-vehicle vendors and general pedestrians, ii) Analyzing the bicycling behavior of commercialized bicycle users (Pathao, Food panda, etc.), iii) Road user's perceptions of safety in the context of non-motorized vehicle movement and iv) Motorcycle Ride Service Providers' Driving Behavior regarding App-based and Contract-based riders.

Abstract

Significant researches have been performed, and policies are adopted concerning Vulnerable Road User's (VRU) safety. However, notable casualties are observed every year resulting from human factors to policy implications. Numerous VRU areas e.g., risk perception of vehicle-to-vehicle vendors alongside general pedestrians; behavioral differences of commercialized cyclists and motorcyclists than the general ones; safety issues of non-motorized vehicles from other road users' perceptions; etc. still need to be explored. This study aims to contribute to existing VRU literature by risk perception analysis of vehicle-to-vehicle vendors and general pedestrians; study of the perceived safety behaviors of commercialized bicyclists and motorcyclists; and identification of key factors influencing risk perceptions of different road users on non-motorized vehicle movement e.g., cycle rickshaws. Data were collected from different residential, commercial areas of Dhaka city and the data collection process was conducted based on well-structured questionnaire. A Bayesian approach was opted to develop four separate models for four user groups e.g., pedestrians, bicyclists, NMVs and motorcyclists to unveil the relevant underlying factors with aid of conditional probability. From the self-reported data, risk categories were defined and classified for respective target variables. Results obtained from the analysis of the models showed that vendors have a 24% high risk perception than pedestrians where gender and education are the most significant variables that influenced risk taking tendency. Basic demographic factors influence the attributes of commercialized bicyclists most significantly. The NMV model predicted that location of NMV stops and existence of pavement hazards on the roads encourages higher risk perception towards NMVs on our roads. Risk perception of road users also varies among various socio-demographic segments like- education level, gender, age, etc. According to the sensitivity analysis of the motorcyclist model; age, gender, driving license status, and trip variations are the most important factors in driving behavior. In spite of the possibility for self-reporting bias, results from this study can be a useful resource for policy makers and law enforcement authorities to take necessary actions in increasing positive safety attitudes among the aforesaid road user group.

Keywords: VRU, Pedestrian, Commercialized Bicyclists, NMV, Motorcyclists, Safety Perception, Bayesian Network, Developing country.

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List of Acronyms

VRU	Vulnerable Road Users
AUC	Area Under the Curve
BBN	Bayesian Belief Network
DAG	Directed Acyclic Graph
EM	Expectation Maximization
FGD	Focus Group Discussion
PC	Peter and Clark
RTA	Road Traffic Accident
ROC	Receiver Operating Characteristic
SDG	Sustainable Development Goals
SEM	Structural Equation Modelling
WHO	World Health Organization
NMV	Non-Motorized Vehicle
MRBQ	Motorcycle Rider Behavior Questionnaire
NHTSA	National Highway Traffic Safety Administration
ANN	Artificial Neural Network
FOB	Foot over bridge
MLR	Multilinear Regression Model
OPM	Ordered Probability Model
LMM	Linear Mixed Model
GLMMS	Generalized Linear Mixed Model
CI	Conditional Independence
PBQ	Pedestrian Behavior Questionnaire

<u>SECTION 1:</u> ANALYZING THE RISK PERCEPTION BETWEEN VEHICLE-TO-VEHICLE VENDORS AND GENERAL PEDESTRIANS

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

Annually, 1.35 million people are subjected to road fatalities worldwide; and 50% of them are Vulnerable Road Users (VRUs)(World Health Organization(WHO), 2018). Pedestrians are considered as one of the most vulnerable road users, comprising 65% of the total road crash mortality across the globe (Xu et al., 2013). In the US, pedestrian deaths have seen a 46% increase in the past decade (4,457 in 2011 to 6,516 in 2020), which is 17% of the total traffic mortality (Stewart, 2022).

According to National Highway Traffic Safety Administration (NHTSA), a key reason of pedestrian crashes is their unpredictable behavior (National Highway Traffic Safety Administration & US National Department of Transportation, 2008). Studies also demonstrate that pedestrians prefer not to abide by the traffic rules (Zhuang & Wu, 2011). Previous findings suggest that pedestrians are the most flexible and fast to respond among the VRUs, yet they are the most unpredictable in nature and can't be supervised via regulations (Jian et al., 2005).

Numerous studies have been conducted over the years to understand pedestrian behavior for reducing pedestrian mortality. Frequency of boarding and alighting was used for assessing pedestrian safety at bus stops, from a behavioral perspective (Kraidi & Evdorides, 2020; Ulak et al., 2021). The studies concluded that the volume of pedestrian crossing and violations along with variation of the speed of the traffic flow are significant variables associated to potential pedestrian collision. Similar studies directly addressed pedestrian boarding and alighting behavior at urban railway stations and bus stops (Qu et al., 2022; Xue et al., 2022). Findings showed that pedestrians past behavior was significantly explaining the tendency of taking risk (42% variance explained), which is higher than % variance explained by attitude and social-factors.

Pedestrian crossing behavior at target locations (e.g., signalized/ unsignalized intersections, junctions, etc.) were addressed in a significant number of studies, via univariate analysis & logistic regression (Aghabayk et al., 2021; Koh et al., 2014; Zare et al., 2019). Male pedestrians had prominently high crossing speed and people crossing with a companion was 246% less likely to take risk than people crossing alone. Another research also used logistic regression for analyzing pedestrian crossing behavior for traffic facility (foot-over bridge (FOBs)) in Columbia (Oviedo-Trespalacios & Scott-Parker, 2017). Only 18% of the pedestrians were preferring to use FOBs in Columbia. Pedestrian crossing behavior was assessed at unmarked roadways in China in 2011 (Zhuang & Wu, 2011).

Illegal crossing/ jaywalking is a prominent feature of pedestrian crossing behavior. Previous researches evaluated pedestrian jaywalking behaviors at X & T junctions in South India and major arterial roads in Qatar (Santhosh et al., 2020; Shaaban et al., 2018). Pedestrians attempted risky crossing during morning and evening peak hours in India. In Qatar 98% of the male pedestrians were performing illegal crossing/jaywalking. The studies also suggested that pedestrians waited for suitable gaps before starting jaywalking.

Bangladesh is a South Asian country with a very high traffic mortality. From 1998 to 2008 a total of 13,516 pedestrians died due to traffic crash in the country (Pasha et al., 2015). However, the death toll is drastically rising in the recent years. In the year of 2020 and 2021, 5,431and 6,284 people died from road accident respectively, which is estimated to be a TK 9,631 crore loss of human resource (Dhaka Tribune, 2022).

Most of the studies in Bangladesh are related to pedestrian behavioral assessment. Study regarding pedestrian’s perception towards road crossing facility (e.g., FOBs, underpass, etc.) demonstrated that only 29% pedestrians preferred FOBs (Pasha et al., 2015). Effects of mobile phone use, using Bayesian Belief Network (BBN) on illegal crossing and factors affecting pedestrian jaywalking strategy in Dhaka City were evaluated in 2020 and 2021 (Prema et al., 2021; Zafri et al., 2020a). Artificial Neural Networks (ANN) was the approach methodology for understanding pedestrian jaywalking behavior at mid-blocks, results showed female pedestrians were more prone to crash than male pedestrians while illegally crossing (Anik et al., 2021).

Hawkers are an integral part of Bangladesh’s economy and traffic system. More than 150,000 hawkers operate in the busy capital Dhaka, in areas like Motijheel, New Market, Baitul Mukarram etc. Their contribution to the GDP is small however, their contribution to the urban economy is crucial for development (Ullah, 2020).

Despite contributing to urban economy, hawkers create nuisance for general pedestrians. They cause encroachment issues, which discourage pedestrians to use FOBs or underpass (Pasha et al., 2015) and force them to jaywalking (Anik et al., 2021). Unsuccessful jaywalking attempts increase the risk of potential crash (Shaaban et al., 2018).

In addition, hawkers are also being killed in traffic accidents (The Daily Star, 2021; The Independent BD, 2018). Due to lack of proper survey and statistics the actual numbers of crash fatalities and injuries of hawkers are not known.

Over the years, several research on improving pedestrian safety have been done. None of the studies addressed hawkers/vehicle-to-vehicle vendors from the perspective of behavior. One of the studies focused on the impact of roadside vendors on pedestrian flow characteristics (Hagos et al., 2020). Yet, the study didn't analyze the impact from a safety stand point.

Due to lack of studies specifically targeting hawkers/vehicle-to-vehicle vendors, previous researches addressing pedestrian behavioral assessment have been considered as the foundation for this finding. Different studies have been performed for identifying factors influencing risk taking behaviors of pedestrians (Marisamynathan & Vedagiri, 2018; Russo et al., 2018). However, the methodological approaches (Multiple linear regressions, Correlation Tests etc.) used in these studies fail to unveil the causal relationships among the factors. Thus, it is important to understand the causal dependencies among variables to truly assess the risk-taking tendency of the two target groups (pedestrians and hawkers).

Causal relationships depend on prior beliefs; thus, Bayesian Belief Network (BBN) has been used to develop casual relationships between variables using conditional probability. BBN is capable of finding the optimum pattern of connections to predict the target variable. BBN can assess the data structure and swiftly search for the strongest connections. In addition, there is very little impact due to introducing new variables to the network as BBN only looks for interdependencies. Therefore, BBN can develop a fully parameterized model that can effectively and efficiently calculate any nodes posterior probability provided with specific evidence (Dai et al., 2021).

1.2 Purpose and Objectives

Understanding and comparing the risk perception i.e., risk-taking behavior (Brewer et al., 2004) of pedestrian and vehicle-to-vehicle vendors is crucial for policy making and improving overall pedestrian safety. The study focuses on analyzing the risk perception of pedestrian and vehicle-to-vehicle vendor by identifying the causal factors (and their relationship), which affects the risk perception of the two target groups in the context of a developing country, Bangladesh. The objectives are,

- Identifying the pivotal factors that impact risk perception of the two target groups (pedestrians and vendors).

- Discovering the causal relationships between the factors based on conditional dependency based on the two target groups and comparing the risk perception of the target groups.

- Recommending relevant policies to assist the policy makers for enhancing overall pedestrian safety and accommodating vendors in the total traffic infrastructure in the context of a developing country.

1.3 Scope of the Study

The research targets analyzing the risk perception by discovering the important parameters, for the target groups. The respondents were interviewed from different parts of the capital, Dhaka for ensuring diversified response from different localities of various demographics.

1.4 Thesis Outline

The thesis contains six chapters. A brief description of the chapters is provided below,

Chapter 1: **Introduction**- The chapter contains background & motivation, problem statement, purpose & objective and scope of the study.

Chapter 2: **Literature Review-** The chapter discusses the relevant literatures, which aided in creating the research workflow.

Chapter 3: **Study Area & Data Collection-** This chapter focuses on the scoping, bounding & acquiring methods of the data.

Chapter 4: **Methodology-** The chapter discusses the progressive workflow of the study and explains the selected method for analyzing the obtained data.

Chapter 5: **Analysis & Results-** The chapter demonstrates the analysis of the data and interprets the computed results.

Chapter 6: **Conclusion and Recommendations-** This chapter depicts the key research findings and suggests appropriate policy implications.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Studies conducted in Bangladesh did address the behavioral aspect of pedestrians from the aspect of risk and safety. However, no studies included the vendors as the target group for assessment. The chapter includes studies from global and regional perspectives, assessing pedestrian risk perception at different target locations and scenarios.

2.2 Risk Perception – Global Perspective

According to Ma et al., (2020) demographic variables highly influence risk taking tendency. Age, education & level of income impacts pedestrian crossing maneuver according to the paper. The objective of the research was to analyze the illegal crossing behavior at signalized intersection for crossing at red lights and outside the crosswalks. A Bayesian approach was adopted for understanding the crossing behavior. Results suggested that, younger generation and people with lower educational qualification & lower income tended to have a very high-risk perception. Number of companions was also a key parameter that impacted risky crossing decisions. The study showed that people with higher companions did not commit to illegal crossing at high-risk target locations (i.e., intersection, junction etc.). In addition, people who were in a hurry took 50% more risk while crossing.

Pedestrians' preference for crossing depends on preferable gap opportunities on the road. A study accomplished by Shaaban et al., (2018) showed, 40% of the pedestrians waited and crossed when there were suitable gaps. The purpose of the study was to understand pedestrian crossing at major arterials. The study adopted multi linear regression (MLR) model for explaining the variables. Results showed that female & elderly pedestrians have considerably slower crossing speed. Variation in crossing speed wasn't affected by carrying of bags or use of cell phones.

Assessing pedestrians illegal crossing behavior & safety in China was key the goal of the study by Zhuang & Wu, (2011). Results showed, heterogeneous and varying speed of traffic flow hindered pedestrians to jaywalking maneuver by blocking the gaps. Hence, in reality, the pedestrians cannot perform illegal crossing by shortest path. However, shortest path crossing is the safest option for pedestrian jaywalking, as it will have the least exposure time to road dangers for the pedestrians.

Traffic volume was found to be positively co-related to pedestrian crash (Xie et al., 2018). The study used a Bayesian approach for developing pedestrian crash model at signalized intersection. The variables used in the study were geometric design, traffic flow characteristics, signal control and built environment.

Insubordination behavior of pedestrians is found to be a significant factor in possible crash at intersections (Marisamynathan & Vedagiri, 2018). The researchers focused to a develop model on the basis of pedestrian crossing behavior at signalized intersections. The study used an ordered probability model (OPM) as previous conventional regression model failed to capture the actual scenario. Results demonstrated that 60% of the pedestrians do not prefer to comply with the rules. 46% performed risky crossing, reason being they were in a hurry. Education and occupation highly influenced pedestrians' noncompliance behavior.

Another study done by Koh et al., (2014), in Singapore, showed, crossing lanes, gender, crossing length, number of passing vehicles etc. were prominent factors contributing to pedestrian incompliance behavior. The study opted for logistic regression for understanding pedestrians' safety violation behavior. Safety was assessed based on personal, situational and environmental characteristics.

Deb et al., (2017) found that, 66.67% of pedestrians did not check both sides before crossing & 16.1% did not look for incoming vehicles, while crossing at unlawful locations. The objective of the study was to evaluate pedestrians' behavior at crosswalks by implementing multiple logistic regressions.

Aghabayk et al., (2021) performed pedestrian risky behavioral assessment both in signalized and unsignalized intersections. The study used liner mixed model (LMMs) and generalized linear mixed model (GLMMs). One of the key findings of the study was grouped jaywalking was found to be riskier than ungrouped jaywalking. Another peculiar finding from the study was, elderly pedestrians were less cautious in unsignalized crosswalks than signalized intersections.

2.3 Risk Perception – Bangladesh's Perspective

Studies conducted in Bangladesh assessed the risk behavior from the light of a developing country. The researches targeted pedestrian perception towards road facilities as well as crossing and jaywalking behaviors.

Study conducted by Pasha et al., (2015) in Dhaka city demonstrated that respondents reported presence of hawkers was one of the key reasons for not using FOBs or underpass. Poor lighting facilities also discouraged them to use these facilities during the night, security being a major concern. 61% pedestrians reported that, using road-crossing facilities was time consume. The study used questionnaire based on Likert-scale. Most of the variables of the study were demographics such as, age, gender, level of income, dwelling condition etc.

Impact of cell phone was also assessed. Gender, jaywalking activities, frequency of cell phones uses were some of the significant factors (Prema et al., 2021). The research used a Bayesian Belief Network for modelling purpose. The objective was to analyze the effect of cell phones on jaywalking behavior of pedestrians. The study concluded that male pedestrians, aged 26-40 with secondary education were susceptible to jaywalking.

Zafri et al., (2020) identified factors affecting pedestrians' decision to illegally cross by the rolling gap strategy. The study used a binary logistic regression model developed in SPSS software. Variables included demographics, intersection control type, available gaps etc. The study concluded that, age was the most significant variable. Additionally, pedestrians crossing in alone showed higher tendency performing rolling gap strategy than pedestrians who crossed in pairs. Some major limitations of the study were not incorporating variables like pedestrian psychology, education, mental process, attitude, and perception regarding situation, safety, and risk.

A recent study by Anik et al., (2021) assessed pedestrian jaywalking at mid-blocks. The study used artificial neural networks (ANN) as the methodological approach. Variables included pedestrian behavioral, demographic, and roadway characteristics. However, the study did not include age level of the target group. The study concluded, women encountering more near crash events than male pedestrians and are more prone to crash. Moreover, jaywalkers have been seen to do running at the last phase of jaywalking.

CHAPTER 3: STUDY AREA AND DATA COLLECTION

3.1 Introduction

The study area covered Dhaka, the capital. Participants were interviewed based on two broad classifications of "General Pedestrian" and "Vehicle-to-vehicle Vendor". The questionnaire was identical for both the participant groups.

Figure 1: Study Area: Dhaka City

3.2 Data Collection

The "Pedestrian and Vehicle-to-vehicle Vendor" questionnaire was developed with the aid of previous literature. The questionnaire included questions (& scenarios) related to demographic variables (age, gender, level of income etc.) risk perception, behavior and policy implications. The survey assessed the risk perception under the following criteria(s): "Boarding & Alighting", "Crossing", "Aggressive Behavior", "Jaywalking", "Crash History" & "Accepted Yielding Distance". Questions under the first four risk perception criteria(s) were on Likert-Scale from "never" to "always". Initially a total 1,236 responses were recorded. Partial responses were removed after screening of the data. The final data set included 1,021 responses. For this study, variables related to demographics and risk perception have been used. Descriptive statistics of the responses has been briefly demonstrated in Table 1,

Table 1: Descriptive Statistics of the Survey Response

#	Criteria	SN	Variable	Item	Frequency	Percentage
1	**Demographics**	1	Person Interviewed	Pedestrian	787	77.1
				Vendor	234	22.9
		2	Gender	Male	784	76.8
				Female	231	22.6
				Transgender	6	0.6
		3	Age	<25	266	26.1
				25-35	398	39.0
				35-50	267	26.2
				>50	90	8.8
		4	Education	Illiterate	28	2.7
				No formal Education	53	5.2
				Drop out	331	32.4
				Formal Education	609	59.6
		5	Monthly Income_(BDT)	<20k	489	47.9
				20-35k	414	40.5
				>35k	118	11.6
2	**Boarding & Alighting**	6	Risky Boarding	Always	81	7.9
				Often	95	9.3
				Sometimes	396	38.8

				Rarely	168	16.5
				Never	281	27.5
		7	Risky Alighting	Always	66	6.5
				Often	140	13.7
				Sometimes	336	32.9
				Rarely	170	16.7
				Never	309	30.3
		8	Risky Alighting Midblock	Always	30	2.9
				Often	91	8.9
				Sometimes	337	33.0
				Rarely	282	27.6
				Never	281	27.5
		9	Looking Behind Getting Out of Bus	Always	682	66.8
				Often	178	17.4
				Sometimes	151	14.8
				Rarely	7	0.7
				Never	3	0.3
3	**Crossing**	10	Risky Crossing Barrier	Always	1	0.1
				Often	19	1.9
				Sometimes	101	9.9
				Rarely	115	11.3
				Never	785	76.9
		11	Risky Crossing Broken Traffic Facility	Always	73	7.1
				Often	92	9.0
				Sometimes	480	47.0
				Rarely	226	22.1
				Never	150	14.7
		12	Looking Both Direction Before Crossing	Always	729	71.4
				Often	146	14.3
				Sometimes	113	11.1
				Rarely	11	1.1
				Never	2	0.2
		13	Looking Both Direction Before Crossing When in A Hurry	Always	372	36.4
				Often	40	3.9
				Sometimes	197	19.3
				Rarely	135	13.2
				Never	277	27.1
		14	Risky Crossing Heavy Traffic Flow Bus in Middle Lane	Always	31	3.0
				Often	38	3.7
				Sometimes	196	19.2
				Rarely	199	19.5
				Never	557	54.6

		15	Risky Crossing Medium Traffic Flow Bus in Middle Lane	Always	98	9.6
				Often	107	10.5
				Sometimes	354	34.7
				Rarely	98	9.6
				Never	364	35.7
4	**Aggressive Behavior**	16	Annoyed at Drivers and Hit Drivers	Always	0	0.0
				Often	7	0.7
				Sometimes	218	21.4
				Rarely	210	20.6
				Never	586	57.4
		17	Angry At Other Road Users	Always	1	0.1
				Often	26	2.5
				Sometimes	305	29.9
				Rarely	237	23.2
				Never	452	44.3
5	**Jaywalking**	18	Type of Jaywalking at Free Flow	Grouped	609	59.6
				Ungrouped	412	40.4
6	**Crash History**	19	Near Crash Experience	No	581	56.9
				Yes	440	43.1
7	**Accepted Yielding Distance**	20	Accepted Yielding Distance	< 5 ft	138	13.5
				5 to 7 ft	369	36.1
				7 to 9 ft	279	27.3
				>9 ft	235	23.0

According to Table 1 respondents preferred “Grouped” jaywalking (59.6%) at free flow over “Ungrouped” jaywalking (40.4%). The preference values of “Never” for variables “Risky Crossing Heavy Traffic Flow Bus in Middle Lane” & “Risky Crossing Medium Traffic Flow Bus in Middle Lane” are 56.4% and 34.7% respectively. This decrease of 19.9% is indicating that, the tendency of performing risky crossing increases when the traffic flow shifts from high to medium.

CHAPTER 4: METHODOLOGY

4.1 Introduction

This chapter describes the methodological approach of the research. The purpose of the study was to analyze the risk perception between general pedestrians and vehicle-to-vehicle vendors by understanding the demographic and risk perception variables. Previous literature demonstrated that these variables are often mutually independent and impacted via previous beliefs (Ma et al., 2020). Hence, Bayesian Belief Network (BBN) was the methodology followed for this research.

4.2 Work Flow of the Research

The work flow diagram of the research is demonstrated in Figure 2.

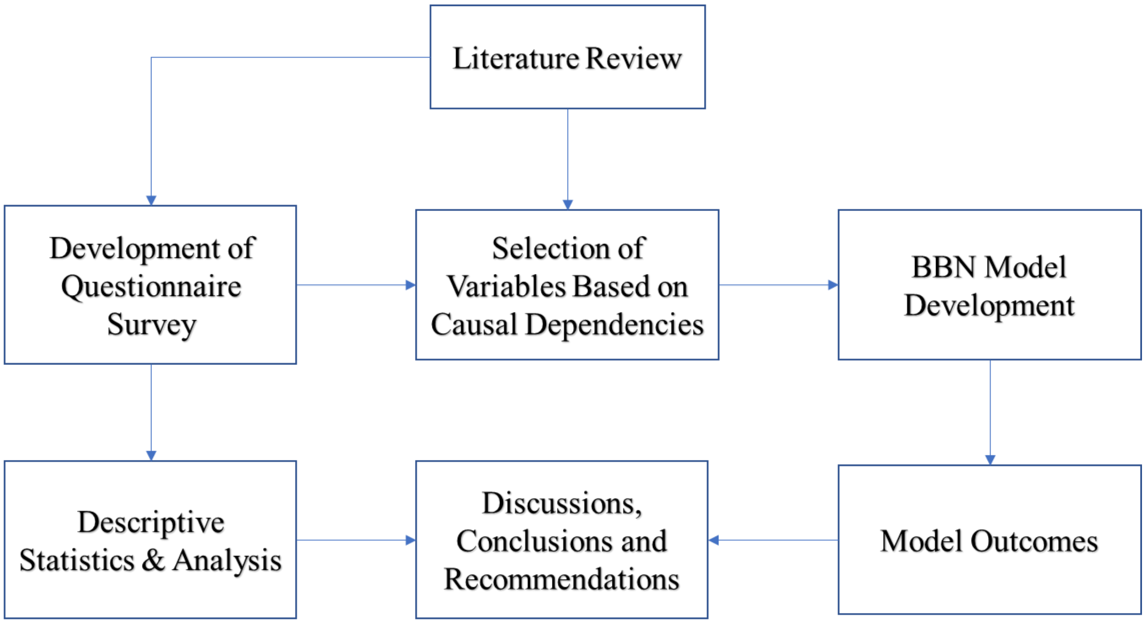


Figure 2: Work Flow Diagram

Initially, literature review was performed for understanding the key findings of the previous literature. Comprehensive & rigorous literature review aided to develop the questionnaire survey. Field surveys were conducted for collecting the data. Then, Bayesian Belief Network (BBN) was created in the form of Directed Acyclic Graph (DAG) using the collected data as input. The model was tuned and optimized based on expert advice, engineering judgements and previous literature. Finally, the model was prepared for analyzing the risk perception between the two respondent groups.

4.3 Bayesian Belief Network (BBN)

Bayesian Belief Network (BBN) was used as the methodology for understanding the hidden connections between the variables and to identify and analyze the risk perception between general pedestrians and vehicle-to-vehicle vendors. Bayesian Belief Network, also known as *Bayes Nets* is a part of the probabilistic *Graphical Models* (GMs) dynasty (Darwiche, 2010). These networks comprise of nodes and edges. Each node representing a variable and each edge represents the probabilistic relationship between two nodes. The final graphical structure demonstrates the knowledge about the unknown dimension. The GMs with undirected edges are named as *Markov Networks*, whereas the directed edges are regarded as the *Directed Acyclic Graph* (DAG). The Bayesian Network is based on the Bayes Theorem (Grover, 2013) which is as follows,

$$P(A|\mathrm{B}) = \frac{P(B|\mathrm{A})P(A)}{P(B)} \quad (1)$$

P(A) and P(B) are the probability of occurrence of event A and event B. P(A|B) is the probability of A occurring when B has already taken place and vice-versa for P(B|A). The Bayesian Nets also includes Conditional Probability Tables (CPT), which demonstrates the probability between two variables. Bayesian Network demonstrates the joint probability distraction, the function for the joint probability is as follows (Stephenson, 2000),

$$P\ (X = X1, X2, \dots., Xn) = \prod_{i=1}^{n} P(Xi|\text{Parents (Xi)}) \quad (2)$$

Expert judgement, previous literature and engineering knowledge were the key components for building the Bayesian Network. The acquired data was use as the input in GeNIe 3.0

Academic Version. In GeNIe, PC algorithm was applied for model development and structural learning of the network at a level of significance of 0.01. The PC algorithm uses Conditional Independence (CI) testing between a pair of variables for creating connections between them (Tsagris, 2019a). Expectation Maximization (EM) algorithm is applied by the software to create the join probability distribution via learning the parameters. The algorithm estimates the maximum-likelihood of the variables from the hidden distribution for the one to many connections (Moon, 1996).

4.4 GeNIe Workspace

GeNIe (Graphical Network Interface) is software developed by University of Pittsburgh. The software is used for decision analysis. It also helps to graphically represent the probabilities of the network. GeNIe is used for analysis of Bayesian Belief Networks.

For this research, GeNIe 3.0 academic version used for formation of the network and learning of the parameters, CPT preparation. Additionally, GeNIe provided various tools for analysis and model validation.

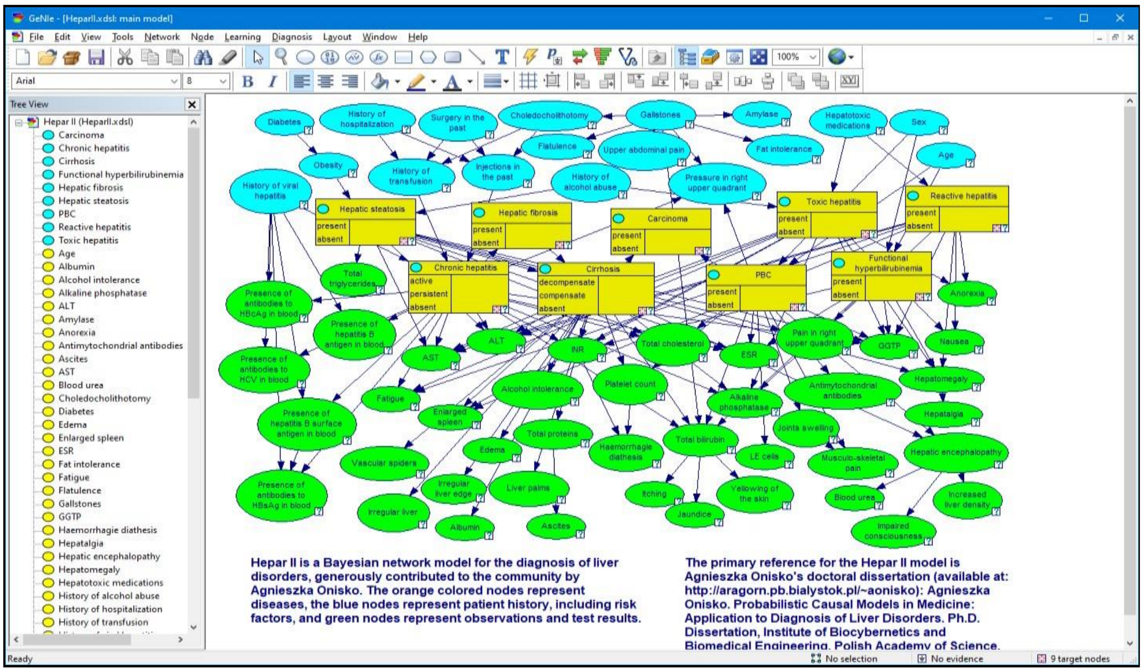


Figure 3: GeNIe Workspace

4.5 Model Development

Initial structural network was created with the PC algorithm in GeNIe 3.0 Academic Version at a significance level of 0.01. Variables under “Boarding and Alighting” and “Crossing” were merged as single variables named “Risky Boarding and Alighting” and “Risky Crossing”. The final model was built after numerous trail and errors based on previous literature, engineering judgement and expert advice. The final model is as follows,

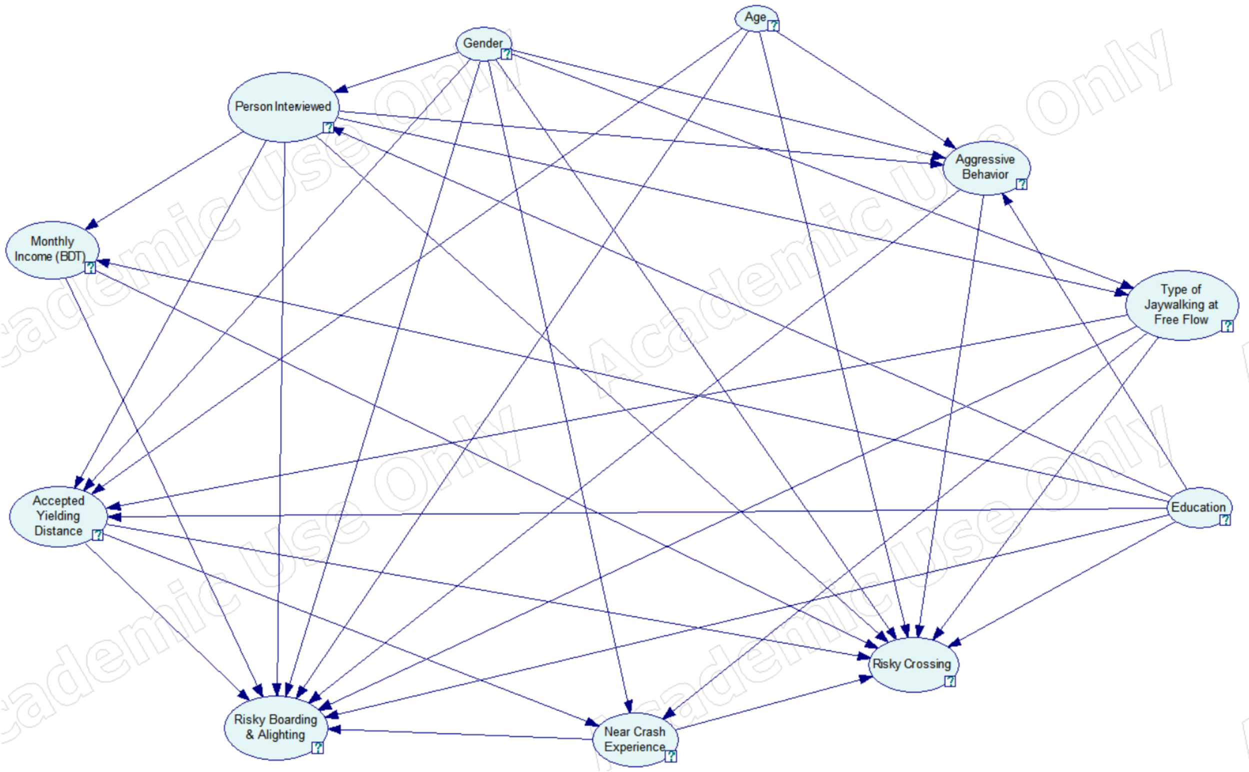


Figure 4: Final BBN Network – Pedestrian and Vehicle-to-vehicle Vendor

4.6 Model Validation

Model validation was performed with the aid of GeNIe tool. Leave One Out (LOO) method was used for model validation. LOO is one of the most efficient methods for cross-validation of data set and developed network, it trains the network except the target variable. Evaluation results are demonstrated as Receiver Operating Characteristics (ROC) curve. The curve plots True Positive Rate vs False Positive Rate. The diagonal line represents 50% accuracy of prediction. Area Under the ROC Curve (AUC) value ranges between 0 and 1. An AUC value of 1.0 represents the test has no imperfect discrimination and AUC value is a measure of accuracy of the model (Hoo et al., 2017). Hence, the value closer to 1.0 represents high model accuracy. However, in practice, AUC value greater than 0.7 is an acceptable value of model evaluation. AUC value for target variables “Risky Boarding and Alighting” and “Risky Crossing” were 0.8419 and 0.825 respectively, indicating a good model validation.

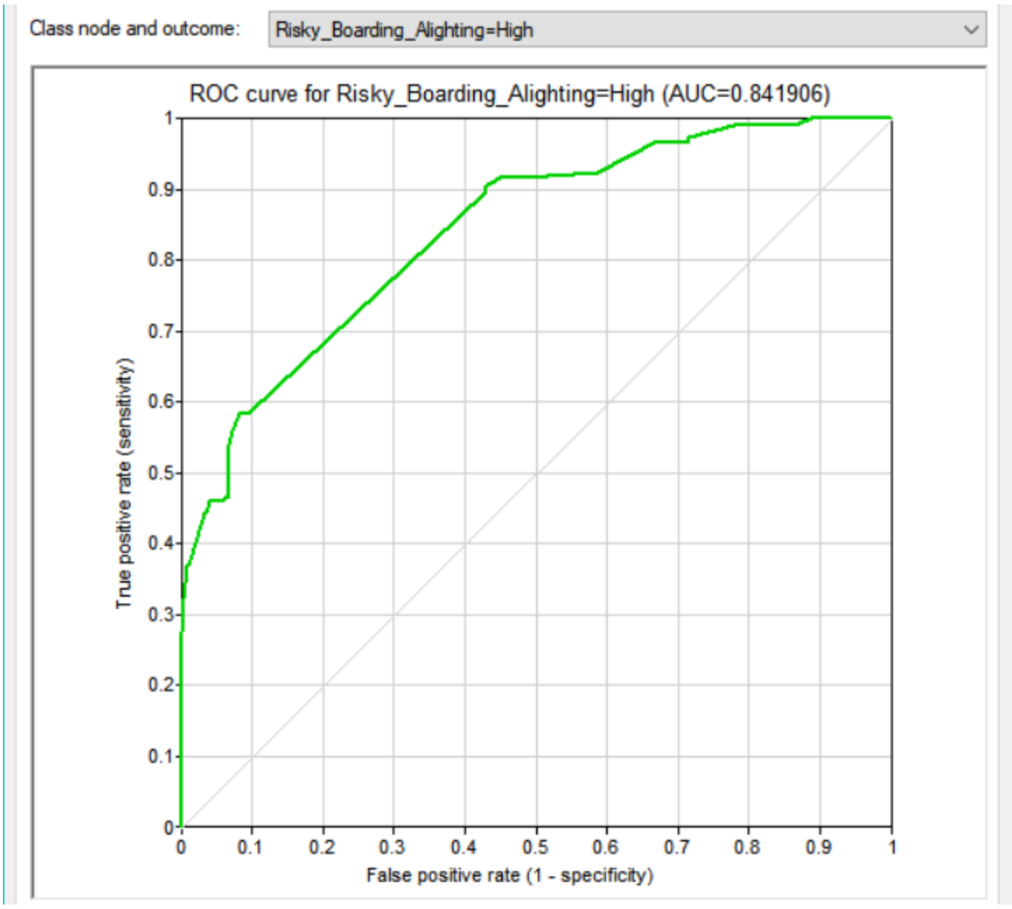


Figure 5: ROC curve for "Risky Boarding & Alighting"

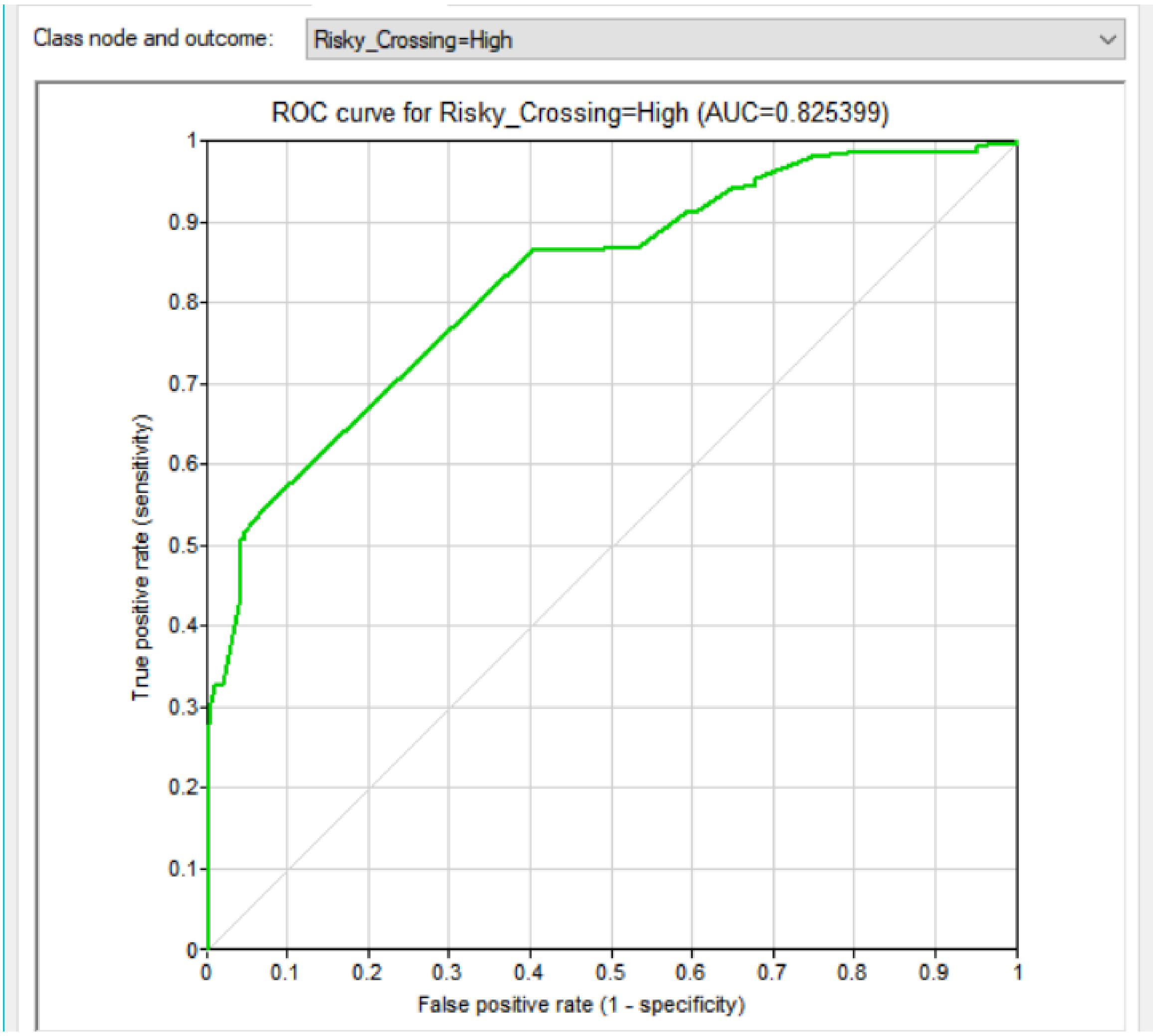
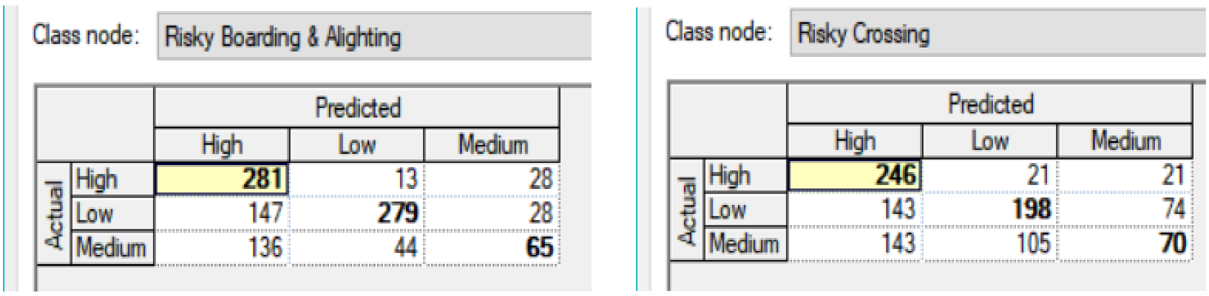


Figure 6: ROC curve for Risky Crossing

The confusion matrix generated by GeNIe visualizes the model performance. Rows represent the actual class and the columns represent the predicted class.



Class node: Risky Boarding & Alighting

		Predicted		
		High	Low	Medium
Actual	High	**281**	13	28
	Low	147	**279**	28
	Medium	136	44	**65**

Class node: Risky Crossing

		Predicted		
		High	Low	Medium
Actual	High	**246**	21	21
	Low	143	**198**	74
	Medium	143	105	**70**

Figure 7: Confusion Matrix for the Target Variables

CHAPTER 5: ANALYSIS AND RESULT

5.1 Introduction

Findings of the research have been demonstrated is this chapter after analyzing the data using the BBN model. The data obtained from the survey was re-classified and re-structured. Variables under “Boarding & Alighting”, “Crossing” & “Aggressive Behavior” were merged as single entities, primarily classified into three groups as per total score, high (upper quartile), medium (between upper and lower quartile) and low risk behavior (lower quartile). The variables were renamed “Risky Boarding & Alighting”, “Risky Crossing” & “Aggressive Behavior”. The calibrated data was then used as the input for initially creating the BBN structure. Several examinations and evaluations were performed for understanding the effects of the parameters on the target variables. Sensitivity analysis and tornedo diagrams were the analysis conducted on the final BBN structure. Model validation was done using GeNIe’s built-in model validation option. Findings of the research were accumulated and presented in tabulated format in this chapter after finishing the analysis.

5.2 Model Analysis

The first step of analysis was learning of the parameters in GeNIe, using the default EM (Expectation-Maximization) algorithm. The built structure in GeNIe represented the marginal probabilities of the nodes. “Risky Boarding & Alighting” and “Risky Crossing” were set as the target variables.

The analysis was performed in two steps. For the first step the target variables were changed to see their impact on the network. In the second step, person interviewed was varied to observe the risk perception of the target groups.

5.3 Analysis for Target Variables Evidence Set from (Low to High)

“Risky Boarding & Alighting” and “Risky Crossing” evidence were set from low to high. The figures below are representing the prior marginal probabilities of the network, and the posterior probabilities for the two evidences.

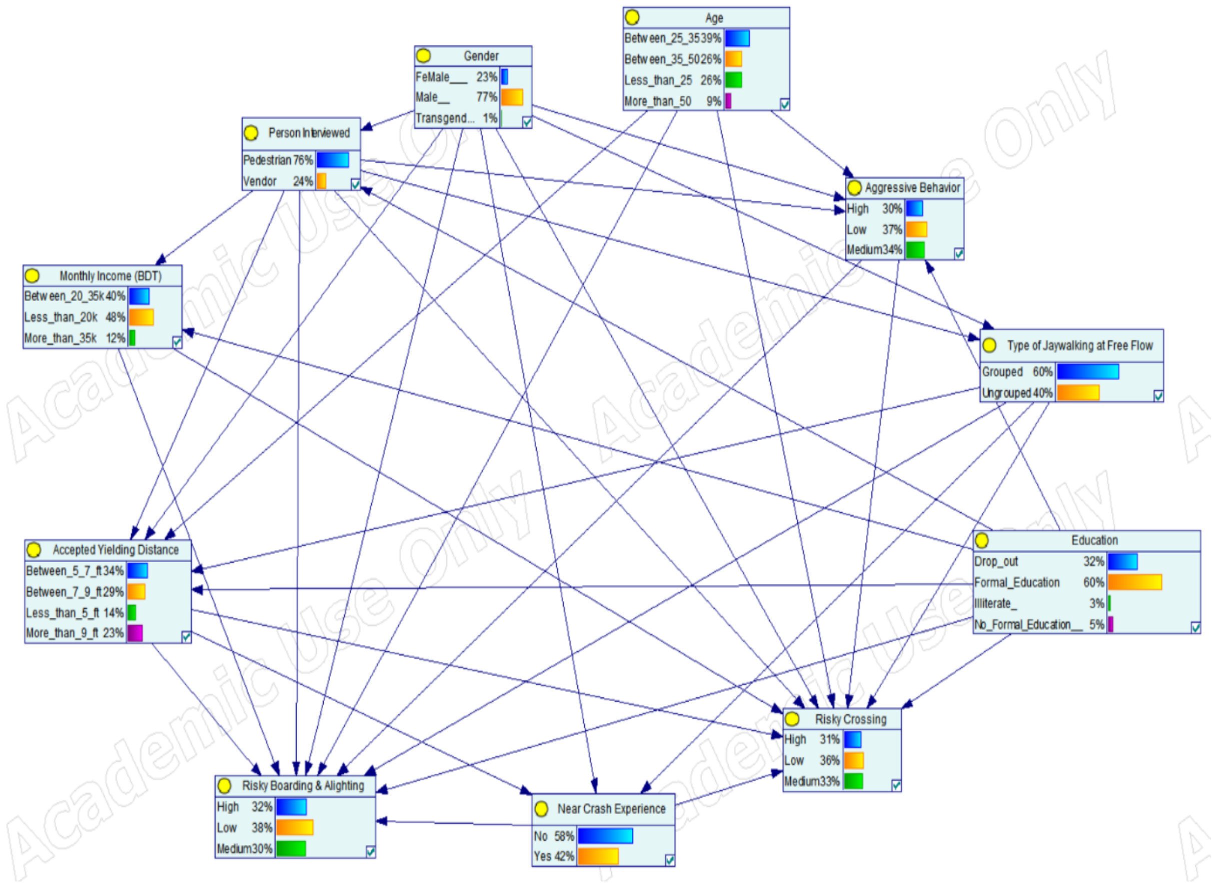


Figure 8: Prior Marginal Probability Distribution of the Network

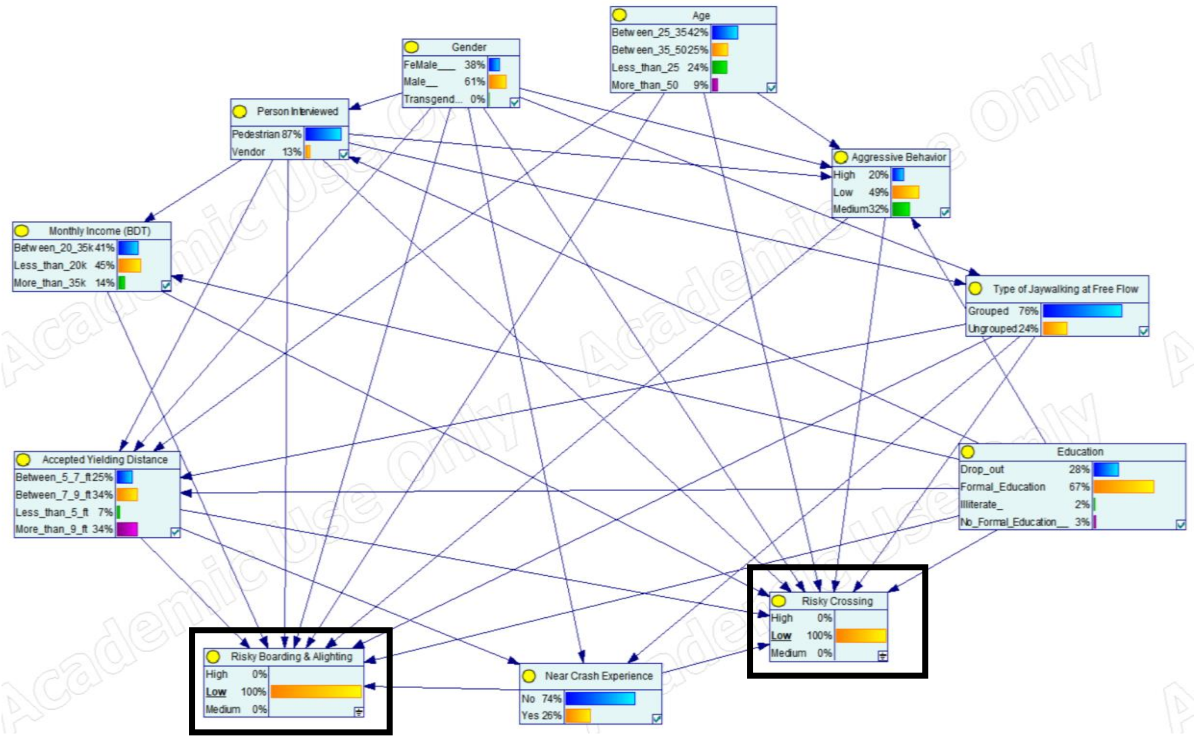


Figure 9: Posterior Probability Distribution for Target Variables Evidence Set to "Low"

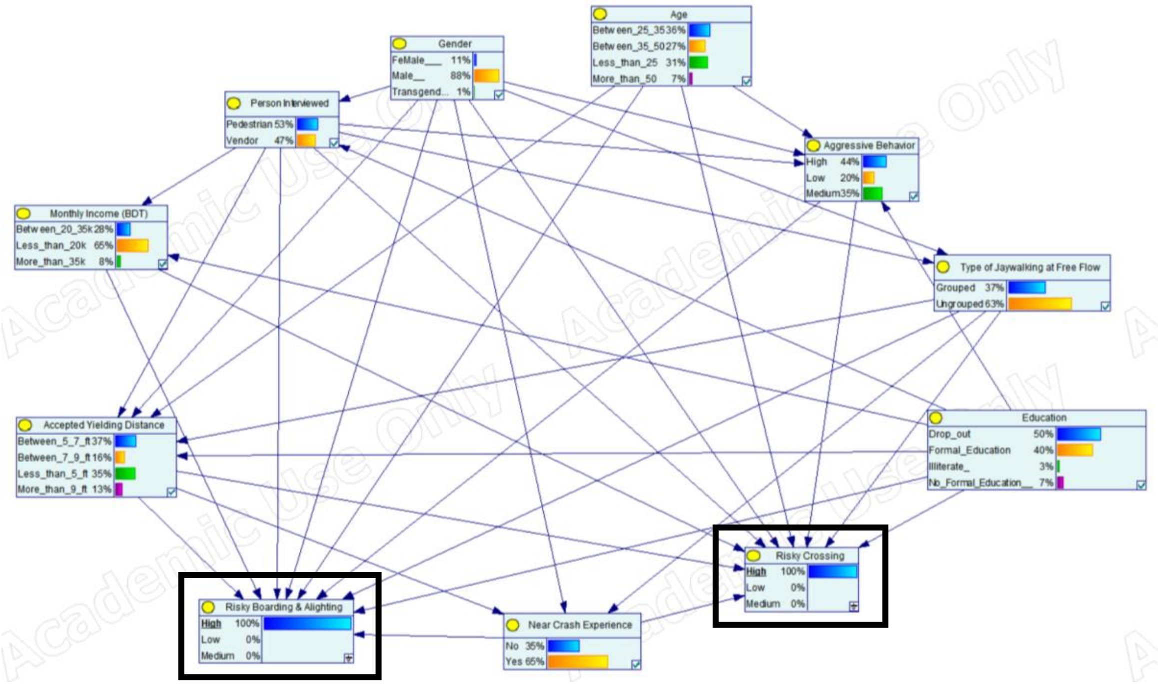


Figure 10: Posterior Probability Distribution for Target Variables Evidence Set to "High"

The posterior marginal probabilities for all the nodes have been represented for both “Low” and “High” evidence in the following table,

Table 2: Marginal Probabilities of All Nodes for Evidence of Target Variable Set from Low to High

Variable	**Variable Attribute**	**Evidence (%) (Target Variables: 100%)**	
		Low	**High**
Person Interviewed	Pedestrian	87	53
	Vendor	13	47
Gender	Male	61	88
	Female	38	11
	Transgender	0	1
Age	< 25	24	31
	25-35	42	38
	35-50	25	27
	>50	9	7
Education	Illiterate	2	3
	No formal education	3	7
	Drop out	28	50
	Formal Education	67	40
Monthly Income (BDT)	<20k	45	66
	20-35k	41	28
	>35k	14	8
Type of Jaywalking	Grouped	76	37
	Ungrouped	24	63
Near Crash Experience	No	74	36
	Yes	26	66
Accepted Yielding Distance	<5 ft	7	35
	5 to 7 ft	25	37
	7 to 9 ft	34	16
	>9 ft	34	13
Aggressive Behavior	High	20	44
	Medium	32	35
	Low	49	20

Setting the risky behaviors (target variables) from low to high, probability of the person interviewed being a vendor increased by 34%. Chances of the person being a male escalated from 61% to 88%. People with formal education and moderate-income levels were less likely to show high risk perception as the chances dropped by 27% and 13%. At high risk, respondents preferred to perform ungrouped jaywalking (value increased from 24% to 63%). In addition, people having previous near crash experiences have a high-risk perception, as 66% had previous crash encounter at evidence value set to high. Finally, individuals with high-risk perception accepted a shorter yielding distance (<5 ft value increased by 28%) and had a high aggressive behavior (24% increase).

5.4 Analysis for Person Interviewed Set from Pedestrian to Vendor

For the second step of the analysis, the evidence was set from pedestrian to vendor for the variable “Person Interviewed”. The purpose was to check the impact on the target variables subjected to the change.

The following figures shows the posterior marginal probability distribution for evidence set from pedestrian to vendor for variable “Person Interviewed”.

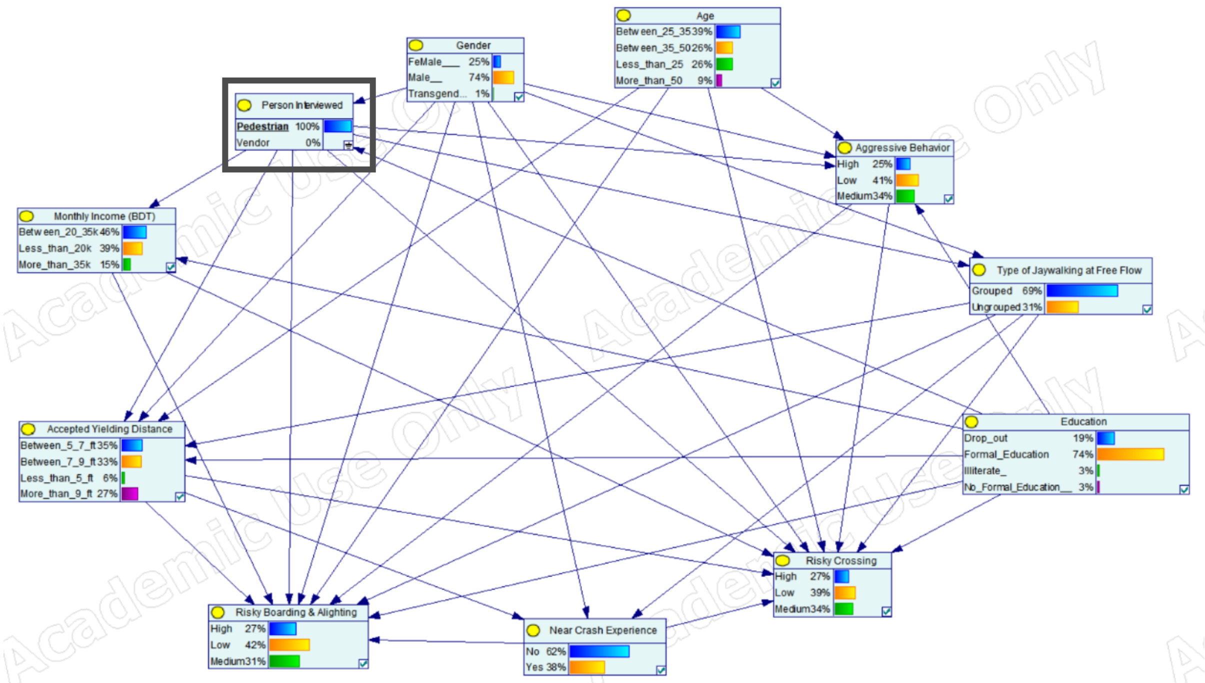


Figure 11: Posterior Probability Distribution for Evidence Value Set to Pedestrian

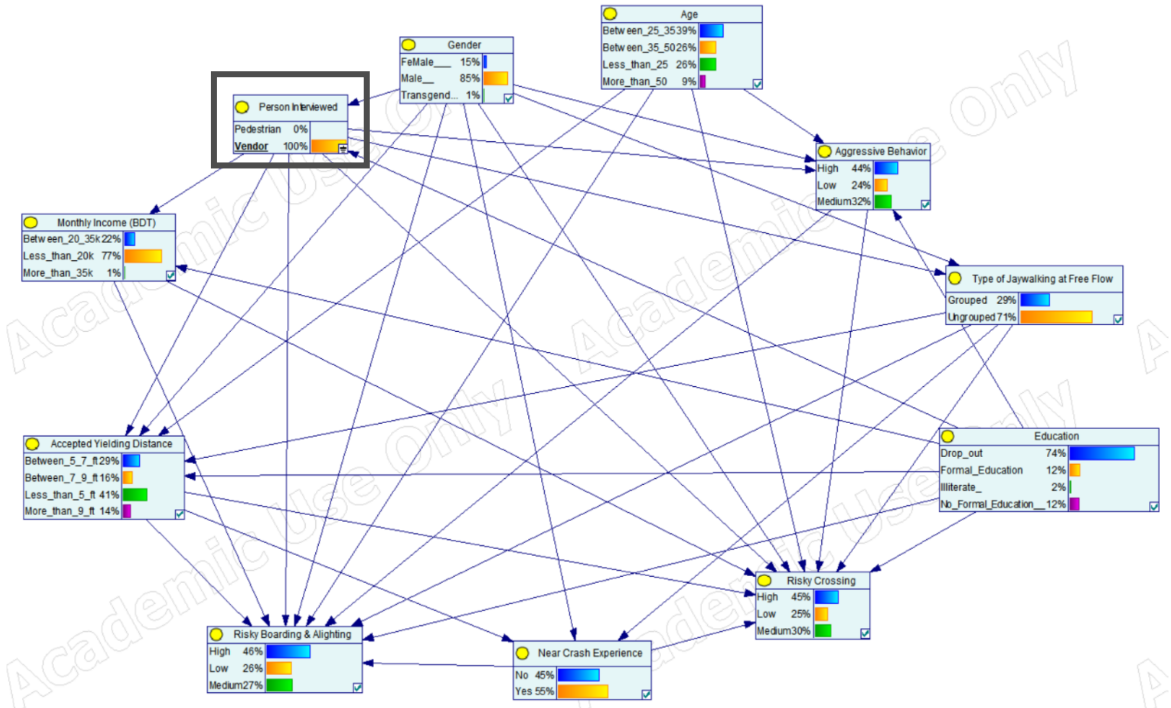


Figure 12: Posterior Probability Distribution for Evidence Value Set to Vendor

The posterior marginal probabilities for all the nodes have been represented for both "Pedestrian" and "Vendor" evidence in the following table,

Table 3: Marginal Probabilities of All Nodes for Evidence Set from Pedestrian to Vendor

Variable	**Variable Attribute**	**Evidence (%) (Evidence Set for Person Interviewed)**	
		Pedestrian (100%)	**Vendor (100%)**
Gender	Male	74	85
	Female	25	15
	Transgender	1	1
Age	< 25	26	26
	25-35	39	39
	35-50	26	26
	>50	9	9
Education	Illiterate	3	2
	No formal education	3	12
	Drop out	19	74

	Formal Education	74	12
Monthly Income (BDT)	<20k	39	77
	20-35k	46	22
	>35k	15	1
Type of Jaywalking	Grouped	69	29
	Ungrouped	31	71
Near Crash Experience	No	62	45
	Yes	38	55
Accepted Yielding Distance	< 5 ft	6	41
	5 to 7 ft	35	29
	7 to 9 ft	33	16
	> 9 ft	27	14
Aggressive Behavior	High	25	44
	Medium	34	24
	Low	41	32
Risky Boarding & Alighting	High	27	46
	Medium	31	27
	Low	42	26
Risky Crossing	High	27	45
	Medium	39	30
	Low	34	25

Setting the evidence from pedestrian to vendor demonstrated 55% increase in drop out under education variable. Also, the person being a male increased from 74% to 85%. Income level group of <20 k value increased by 38%. Preference for ungrouped jaywalking went from 31% to 71%. High aggressive behavior, risky boarding & alighting & risky crossing also increased by 19%, 39% and 18%. In addition, vendors prefer to very short yielding distance while crossing (<5 ft value went from 6% to 41%) and they have a 17% higher history of previous near crash events than pedestrians.

5.5 Sensitivity Analysis

Sensitivity analysis was performed on the model for identifying the most prominent variables. GeNIe shows the variation of impacts of the variables in sensitivity analysis. Variables having the dark red color are the most significant variables. Effect of the variables gradually decreases with the decreasing intensity of red color. Variables with white color have very little impact and variables in grey color have zero impact on the target variables.

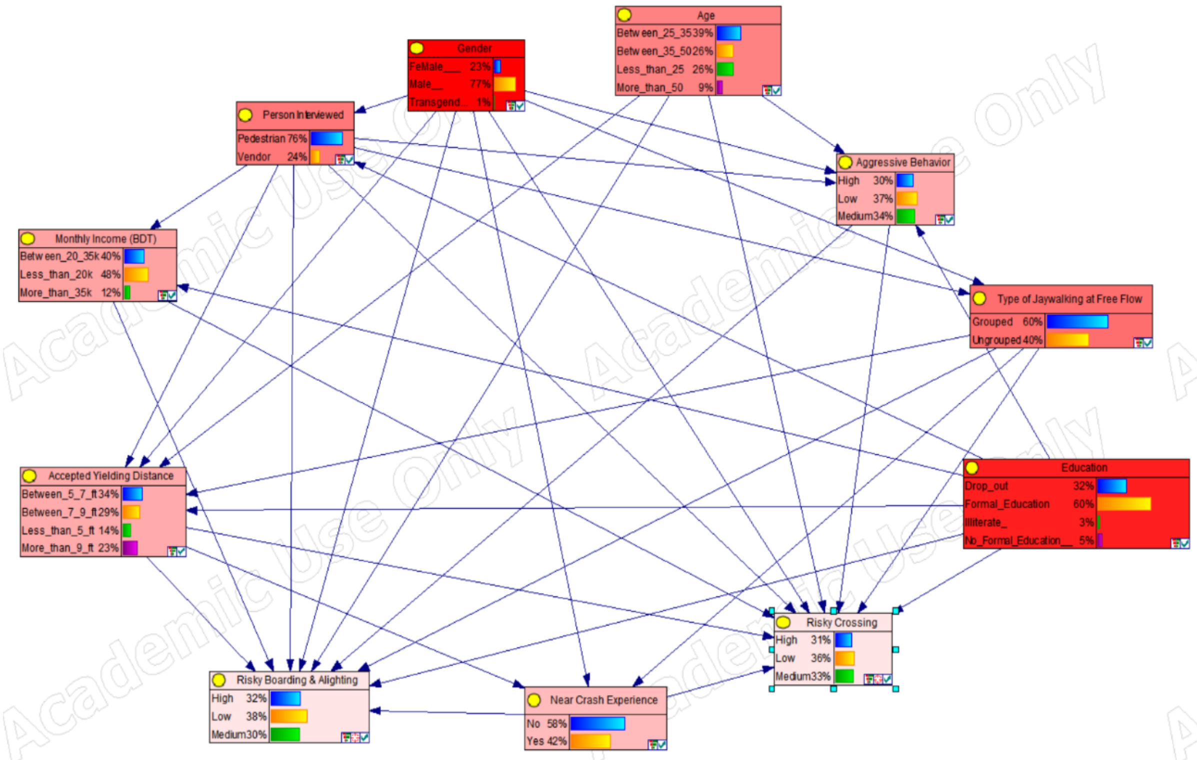


Figure 13: Model Sensitivity

Education and gender are the most sensitive parameters in dark red. Age, person interviewed & Type of jaywalking at free flow are the second most important parameters. Near crash experience and accepted yielding distance are the least sensitive variables in the BBN structure.

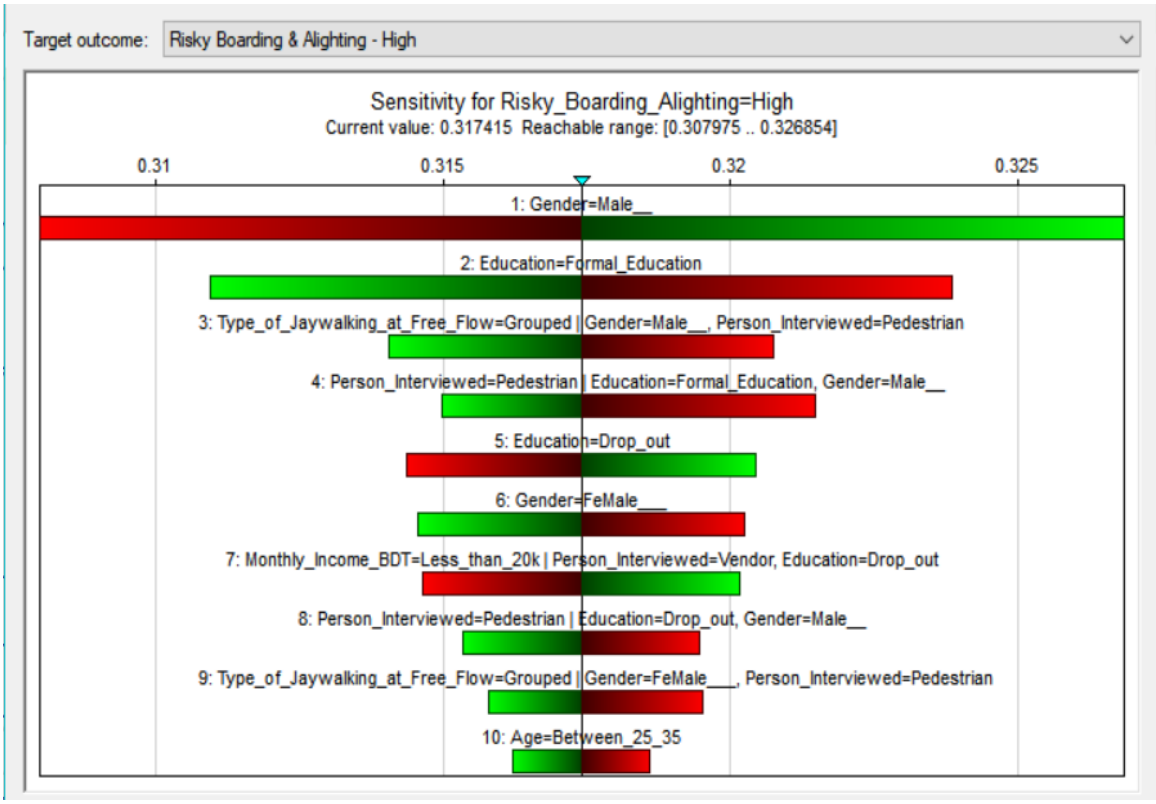


Figure 14: Tornedo Diagram for Risky Boarding & Alighting

The tornedo diagram in GeNIe under sensitivity analysis identifies the most important situation of variables for the chosen state of the target parameter. “Gender = Male” was the most significant on risky boarding & alighting = high. “Age = between 25-35” was the least significant state for risky boarding & alighting = high.

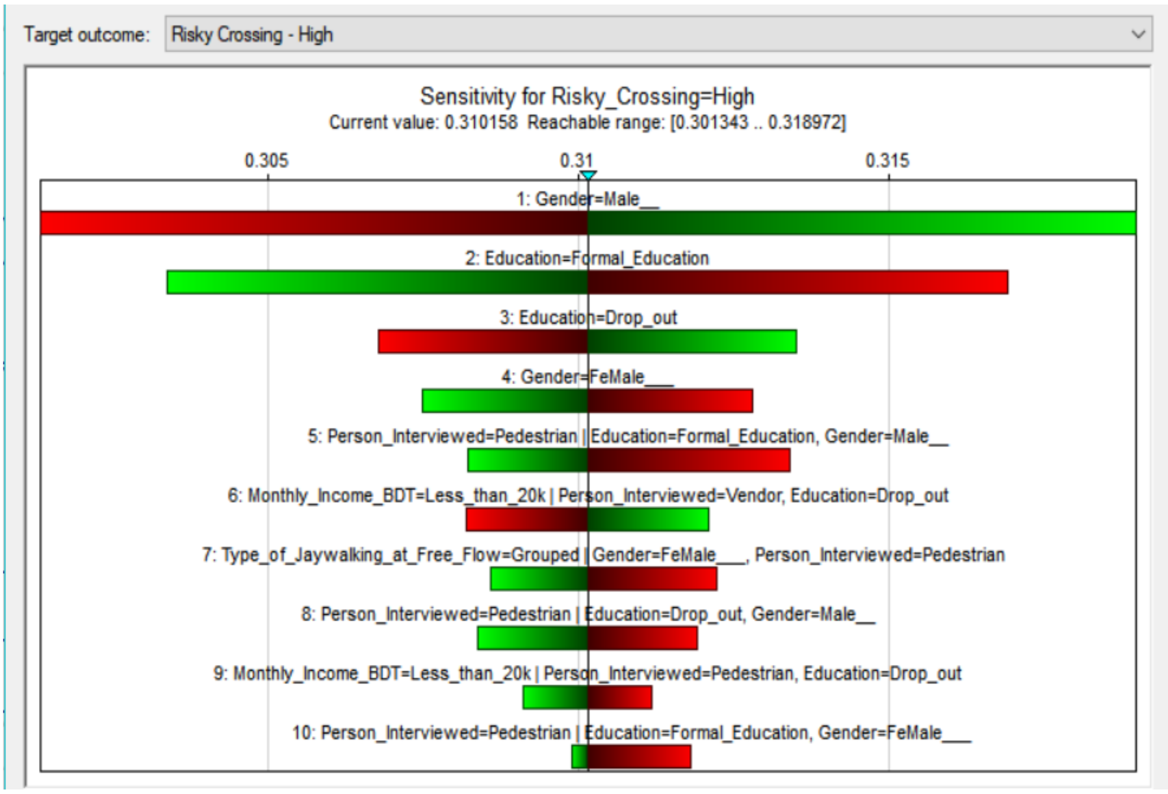


Figure 15: Tornedo Diagram for Risky Crossing

Similar to that of risky boarding & alighting, “Gender = Male” was the most significant on risky crossing = high. However, “Person Interviewed = Pedestrian”, “Education = Formal Education” and “Gender = Female” were the least significant states for risky crossing = high.

CHAPTER 6: CONCLUSION AND RECOMMENDATION

6.1 Introduction

The chapter summarizes the major findings of the study. The chapter also includes associated policy recommendations in conjunction to the outcomes. The proposed recommendations will aid the policy makers and transportation planners to improve pedestrian safety in Bangladesh. In conclusion, the study limitations/gaps and future scopes are outlined.

6.2 Key Findings

6.2.1 Risk Perception

The goal of the study was to analyze the risk perception of vehicle-to-vehicle vendors and general pedestrians. “Gender”, “Education” and “Person Interviewed” are the three most significant and sensitive parameters (as per the tornedo diagrams and sensitivity analysis). Vehicle-to-vehicle vendors have 24% higher risk perception than general pedestrians in critical “crossing” and “boarding & alighting” scenarios. In a broader spectrum, the core characteristics of the vendors (who were prone to crash) are: male, low income and drop out. High aggressive behavior (19% higher) and smaller accepted yielding distance (<5ft 45% higher) were two prominent behavioral difference between the two target groups. Finally, vendors preferred ungrouped illegal crossing at free flow of traffic (40% higher than grouped), which is a contrasting finding, as previous studies suggest that grouped jaywalking was found to be riskier than jaywalking alone (Aghabayk et al., 2021).

6.2.2 Other Findings

Male pedestrians (88%) and pedestrians having previous near crash experience (66%) had a higher tendency of showing risky boarding & alighting and crossing maneuver at pivotal scenarios. They also accepted shorted yielding distance and showed high aggressive behavior. Pedestrians with a medium level of income and proper education were more cautious and took less risk. The findings clearly indicate that, “Gender”, “Education” and “Income” highly affect risk perception of an individual. Only peculiar finding is the previous near crash experience increases high risk-taking tendency; however, it should have been the opposite as people are likely to be more cautious learning from past experience.

6.3 Recommendations and Policy Implications

The study aimed to analyze the risk perception of the two target groups: pedestrians and vendors; and compare the risk-taking mentality. In order to fulfill this goal, questionnaire was developed from the scratch with the aid of literature review. Data collected across the busy capital, Dhaka city as vendor activity is at its peak in the capital. The obtained data was the reorganized and re-categorized. Then the data was fit into the Bayesian network and the network was tweaked and fine-tuned. The findings from the research calls for strong implication of policies. As “Education” was an important parameter of the network and pedestrians with formal education were less likely to violate the rules, introducing campaigns and awareness programs (posters, advertisement, community participation, TV programs etc.) targeting both vendors and pedestrians to make them aware of the risky behavior can be a crucial step (Aghabayk et al., 2021; Anik et al., 2021; Zafri et al., 2020). Similar to pedestrian behavior questionnaires (PBQs), vendors behavior questionnaire can be used as an instrument for self-assessment of risk taking behavior (Deb et al., 2017). Risky boarding an alighting occurs due to lack of not having designated bus stops, hence designated bus stops can reduce the reduce both jaywalking, risky boarding & alighting as well as risky crossing and reduce potential fatal accident (Anik et al., 2021). Turning uncontrolled intersections into controlled intersections using proper traffic signs & signals and road marking was also mentioned in a regional study (Zafri et al., 2020). Fixing broken barriers and median facilities to separate pedestrian and vendor movement from traffic flow can reduce the tendency of risky crossing (Pasha et al., 2015). Additionally, they recommended to build underpass than FOBs will be beneficial. Shedding light on law enforcement will be also be a pivotal move (Shaaban et al., 2018). Creating pedestrian refuges can also be a viable option for mitigating risky crossing maneuvers of vendors and pedestrians (Aghabayk et al., 2021). Finally, segregating vendors and dedicating them with proper street markets on weekends like night markets in Shanghai China, will help mobilizing the country's economy as well as improve overall pedestrian safety (Allison et al., 2021).

6.4 Limitation and Future Scopes

The core idea of the study is novel as none of the regional studies addressed risk perception of vendors. The study identified and analyzed the risk perception of the two target groups by unveiling the underlying risk factors. Moreover, causal relationship among the identified parameters was developed via BBN based on prior beliefs. Hence, the study is one of the first of its kind. Yet, there are some major limitations of the study.

One of the major limitations of the study was the questionnaire was a self-assessed questionnaire; hence, there is a potential of self-reporting bays. Inclusion of scenario-based questions and questions regarding pedestrian policy can improve the quality of analysis and expand the variable domain. Additionally, clustering of the two risk variables under a single risk perception variable could have provided better results regarding risk perception. Active participation from the stakeholders and policy makers is important. Community participation is also a must. In the end, a sustainable financial and economical approach can ensure proper implementation of the recommendations.

<u>SECTION 2:</u> ANALYZING THE BICYCLING BEHAVIOR OF COMMERCIALIZED BICYCLE USERS (PATHAO, FOOD PANDA, ETC.)

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

As the trend of transportation development intensifies, for the increased number of vehicles, the death and injuries resulting from traffic accidents are considered of great concern globally. On a global scale, 1.35 million people die in traffic accidents per annum and thus, traffic accident being the eighth leading cause of death form all age groups (World Health Organization, 2018). More than 50% of the global road fatalities include vulnerable road users. Among all the vulnerable road users, Bicyclists are contemplated to be one of the active mode user who assures sustainable mobility. The growth in number of motorized vehicles and their use in whole world neglect cyclists' need in road design, law enforcement and land use planning which makes the cyclists susceptibility to road traffic crashes and injuries more notable (Geneva: World Health Organization, 2017). It is currently a matter of great concern that, between 2007 and 2015, the rate of cycling-related major trauma hospitalizations climbed by around 8% per year, while the rate of injury-related hospitalizations among other road users decreased. (AIHW: R Kreisfeld & JE Harrison, 2015; Beck et al., 2017). As per Sustainable Development Goal 11, Target 11.2, cycling is highlighted as an accessible mean preferred as transport for majority people (UN, 2021). In current time, around 41000 cyclists are killed each year while cycling for purposes like going to school, work or home, which acts for 3% of total global road traffic death tolls.

When it comes to ensuring sustainable transport development, currently the transport sector provides with 23% of green house gas emissions globally (World Bank, 2017). This industry is also a major source of air and noise pollution, particularly in urban areas, where about 3.7 million people die each year as a result of outdoor pollution (World Health Organization, 2016). As environmental pollution becomes prominent, transport users are more likely to engage green consumption behavior. To prioritize resources required for ensuring sustainability of transport mode, bicycle possesses major health and sustainability benefits. As a result, massive hike in bicycle usage is being observed. In current surge of Covid-19, Europe and America have seen massive rise in bicycle use (175% in Switzerland and 151% in Philadelphia) (The Economist, 2020).

While the selection of mode of transport, the preference of comprehensive safety, sustainability, accessibility, and comfort are mostly triggered by the behavioral perception of the user. Tanzania and Kenya conduced travel behavior analysis of cycling as well as walking In 3 different African cities in 2010 where cycling accounted for only 3% of all transport mode in Dar es Salaam. In Nairobi, many cyclists are deterred from cycling due to trend of road traffic crashes. Bicycling is most popular among commuters from low-income households in Cape Town, where financial limitations prevent them from using other modes of transportation. However, cities in Western Europe, North America, and South America have varied analyses of cycling between 1990 and 2015, as riding levels have increased as infrastructure and policies have been strengthened. (Pucher & Buehler, 2017). Copenhagen and Amsterdam, the cities with high bicycle use, usage rates increased by 10% and 12% respectively in this time span. Also cities with low bicycle use, such as Bogotá (5%), Buenos Aires (3%), and Portland, Oregon (5%), observed large increases (Geneva: World Health Organization, 2020).

Because of Bangladesh's susceptible, diversified, and complicated transportation infrastructure and implied policies on our roads, accidents and road safety issues are common. According to Sustainable Urban Transportation Index, a quantitative analysis of Dhaka city’s transportation has been and interpreted as moderate system with a geometric mean of the index of 46.27 (Noor-E-Alam, 2018). Each year, over 4000 people die in Bangladesh due to road traffic accidents, according to police statistics. Given issues such as underreporting and definitional ambiguities, the real number of fatalities per year is estimated to be between 10,000 and 20,000. Among this high fatality trend, on average 100 bicyclist die each year as per police reports which characterizes 3-4% all road fatalities. The urban areas account for only 32% of accidents whereas rural areas account for 68%. According to the MAAP database of cyclist fatalities in Bangladesh, around 800 fatalities occurred to cycle rickshaws and bicycle in Bangladesh during 1998-2006 representing roughly 12% of all fatalities on urban streets (Md. Mazharul Hoque, S. M. Sohel Mahmud, 2020).

The bicyclist fatality trend is quite crucial considering the lack of official indicators on bicycle ownership, which is between 2-3 million in Bangladesh. According to a survey conducted, it is showed that about 2% h/h own bicycles (Flavia & Choudhury, 2019). In case of modal share, about 6.3% trips were hound to be on a cycle on arterial road sections in Dhaka whereas the modal share of bicycle in medium cities are Sylhet (7.1%), Mymensingh (4.3%) and Bogra (5.2%). The predominant types of bicycle accidents are rear end (58%) and head on collision (21%). In Asia, comparing with low bicycle use, the rate of fatal accidents involving bicyclists are reasonably high. The fatality rates of some of the countries of Central Asia, South and South East Asia are People's Republic of China (92%), Malaysia (62%, 1994), Indonesia (9%, 1991), Sri Lanka (17%). On the contrary, developed countries like New Zealand (3%), Australia (3%) are quite low (Md. Mazharul Hoque, S. M. Sohel Mahmud, 2020).

Typically, transport sector shows particular potential in economic and social development as well as is liable for 5-10% expenditure of GNP and adds to 10-25% of GNP. So on a similar note, the road accidents in Bangladesh are costing the community in the order of Tk. 5000 crore (US $800 million), nearly 2% of our GDP (Hoque & Alam, 2002). To sustain the economic growth, the global expansion of e-commerce particularly online to offline (O2O) is accountable. The most booming area of O2O commerce is online food delivery platforms along with some other online delivery platforms, which ensures economic, social as well as environmental sustainability. Undoubtedly to assure economic sustainability, the online food industries are providing many jobs in the delivery sector (Li et al., 2020). As a result, this sector is significantly evolving the use of bicycling for commercial purpose. For quick delivery, many other modes of transport can be used but considering sustainability and accessibility; bicycles are being used more prominently. Promoting a green image not only raises customer awareness about the environment, but it also helps to build brand equity. (Chen, 2010). More evidently, such a green image impacts consumers' purchasing behavior which positively impacts the commercial purpose (Jeong et al., 2014). Thus, customer satisfaction allows to impact delivery person or particular commercial bicyclists behavior, which impairs safety. The growth commercialized bicyclists, concerns about commercialized cyclist safety have been raised, primarily through online delivery services as they represent a unique group of vulnerable population of road users (Li et al., 2020).

Commercialized cyclist compose distinct demographic, characteristics, behaviors, incident and injury patterns which currently have very much little understanding due to limited research done on behavioral perception. However, such factors are not always mutually independent, and more often, it is the integrated influence of multiple factors affecting the behavioral attributed specifically to reflect on a unique group of users. So, for clear understanding, the causal relationship between unique characteristics of commercial cyclist and considerations regarding commercial fulfillment. As casual relationships are based on prior beliefs, Bayesian theory can be used to establish a relationship among the variables using conditional probability.

1.2 Purpose and Objectives

Identifying the factors that have a greater influence on behavioral attributes of commercialized bicycle users (Pathao, Food Panda, etc.) which calls for proper policy implication to promote safe and active implementation of bicycle usage. Our study attempts to determine the key factors influencing the perceived behavioral attributes of commercialized users of bicycle of a developing country, Bangladesh. The focal objectives of our study are:

- To identify key factors that affecting the behavioral perception of commercialized bicycle users.
- To find out the causal relationship among demographic, commercial characteristics and behavioral intensity factors of commercialized bicyclists based on conditional dependency.
- Recommend relevant policy measures prioritizing bicyclists behavior perception in developing country condition with heterogeneous traffic flow.

1.3 Scope of the Study

The study is done to identify the dominant factors motivating safety restraint use among the drivers and establishing a causal relationship among those factors. The survey covered majority areas of only Dhaka city to form city representative data.

1.4 Organization of the Thesis

The thesis has been organized into six chapters. The chapters are briefly introduced here:

Chapter 1: **Introduction**: This chapter explains the background and motivation, problem statement, purpose, objective and scope of the research.

Chapter 2: **Literature Review**: This chapter discusses the relevant literatures that helped in gaining the most suitable work plan for the research.

Chapter 3: **Study Area and Data Collection**: This chapter sheds light on scoping, bounding and data acquiring techniques.

Chapter 4: **Methodology**: This chapter explains the gradual working process of the research and illustrates the method adapted to analyze acquired data.

Chapter 5**: Analysis and Results**: This chapter discusses the analysis of collected dataand interprets the obtained results.

Chapter 6: **Conclusion and Recommendation**: This chapter presents the major findings of the research and suggests suitable policy implication.

CHAPTER 2: LITERATURE REVIEW

There has been many studies conducted on the behavioral perception of the bicycle users but these perceptions widely vary focusing on the purpose of bicycling. As per the scope of the study, bicyclists who are riding for commercial purpose cohort completely eccentric behavior which currently have very little focus in case of implementation of policies and programs. This chapter starts with focusing on the bicyclists behavioral analysis done globally followed by discussion on bicyclists in Bangladesh and variation in behavior with purpose of cycling.

2.1 Previous Studies on Bicyclists Behavior Analysis

As bicyclists behavioral attributes contributes vigorously in traffic conflicts and other safety features, many study has been performed to analyze those behavioral pattern and act accordingly. According a study conducted in China, the unsafe bicycling behaviors differs based on variation in riding areas as well as type of riders. The dominant incidences which were considered to inspect the variation occurred in presence of personal or shared bicyclist are – not using helmet (99.28%), riding in mixed traffic lane (64.06%), violation of traffic lights (19.57%), following wrong way (13.73%) and not holding the handlebar with both hands (2.57%) (Gao et al., 2020). As a result many implications like efforts in increasing mandatory helmet wearing has been recommended as an effective behavior change tool, reducing cycling-related head injuries by 48% and fatal injuries by 34% (Hoye, 2018). Another survey on shared bicycle riders in same study area showed that proportion of participants who reported riding in a risky manner on a regular or frequent basis represented by 1.1% who were carrying passengers on bicycle whereas 97.6% were not using helmet (X. Wu et al., 2019). Also, according to a Beijing research, 56% of bicycle users traveled through red light signals (C. Wu et al., 2012). According to a study conducted by Wei Du & Jei Wang, concerning rates were observed amongst electric bicycle users in Suzhou, China and the considered unsafe behaviors were, riding in a motor vehicle lane, running red signals, maneuvering in opposite direction of traffic, use of mobile and not wearing helmet while riding (Du et al., 2013).

Jian Wang and Ye Chen (2022) used Bayesian modelling path coefficient diagram to analyze the causal effects of traffic conflicts happened due to variation in riders behavior at intersections. The variables considered in structural modelling are demographic characteristic, waiting time, behavioral intentions, road and traffic conditions and intersection areas which showed that environmental factors have less direct impact on severity of traffic conflicts than human factors (Wang et al., 2022). As per findings of Sun (Sun et al., 2019) and Ravishankar (Ravishankar & Nair, 2018), riders personal properties like gender, age, vehicle etc., significantly effects the tendency towards perceiving dangerous behaviors. Thus, dangerous behaviors such as distractions (Robartes & Chen, 2017), disobeying traffic signals (Salon & McIntyre, 2018), speeding (Behnood & Mannering, 2017) are proven statistically that these influences safety significantly.

A study conducted by Andreas Blitz (2021) showed cycling behavior and the perception of the local environment as well as attitudes using 21 different perceptions as well as demographics, transport mode availability and general travel attitudes. In this study multivariate analysis was done to portray interrelation between the observation of built and non-built environment characteristics and also stage of model of self-regulated behavioral change portrayed the influence of perceptions towards openness and frequency to use bicycle (Blitz, 2021). Another experiment on Spain was done to measure the perceived safety of cyclists and Bayesian ordinal logistic regression model was developed which showed that small lateral clearance and a rapid overtaking speed make riders feel unsafe. (Rasch et al., 2022). Sergio A. Useche (2018) conducted a cross-sectional and exploratory study to determine the discouraging and promising factors behind the use of bikes among cyclists relating with the corresponding crash history. The dominant encouraged factors were found to be fitness (38%), ensuring ecological sustainability (14%), time saving (10%) and economy (13%) whereas the relevant discouraging factors were perceived crash risk (17%), opposing weather condition (17%), lack of safety (16%) (Useche et al., 2019).

2.2 Previous Studies on Bicyclists in Bangladesh

There are little studies done specifically on bicyclists in Bangladesh, which mainly covers behavioral analysis and mode choice behavior. A study on mode choice behavior was conducted using multinomial logistic analysis where the public preference for using bicycle over other para-transit modes in Rajshahi city were stated. As per the analysis considering quantitative variables like travel cost, access time, egress time, waiting time and in-vehicle time, it was found that majority of the people prefer bicycle for travelling and demand for bicycle infrastructure for safe maneuvering (Md. Raihan Gafur, 2017). Combination of multinomial logit model and linear regression models were utilized to understand the time and money saving nature and identify the equivalent benefit of commuter cyclists (Ahmad Ilderim Tokey, Shefa Arabia Shioma, 2020). According to Haroon and Bhakta (2018), the factors those motivated the commuter of Dhaka city to use bicycle transport mode are additional perks, general and personal benefits as well as infrastructural benefits, respectively (Haroon, 2018).

The use discrete choice model has defined the benefits of a bicycle lane by taking into account socioeconomic aspects and cycling-related elements that may influence the respondents' choice of bicycle trip (user and non-user) (Dey et al., 2014). Another research using regression model was done to analyze the complete scenario of students using bicycle in northern part of Khulna city where the potential influencing factors were road condition, heterogeneous traffic flow and bicycle specific infrastructure. Moreover, analyzing the impact of socio-economic parameters where distance travelled had negative impact on trip generation (Sahriar et al., 2020). The highest complained problems of cyclists who were cycling in commercial areas were - safety, scarcity of parking area and not provision of bicycle lane, which were observed among the office going bicycle users in Dhaka city (Shioma et al., 2017).

2.3 Previous Studies on Change in Behavior with Exposure

Considering the general behavior pattern of bicyclists in case of demographics, risky concern, safety and accessibility, many studies has shown that the behavioral perceptions changes accordingly with the purpose of bicycling (commuting, recreational, travel, commercial purpose, shopping or etc.,). Travel survey was conducted midst public bike users in Beijing and found the significant effect of built environment, middle aged and middle income commuters, travel distance on likelihood to use public bicycles as feeder mode for metro transport. In this regard, binary logit model and cluster analysis were done prioritizing route environment, socioeconomic factors and travel distance as variables (Zhao et al., 2022). Another study on Barcelona using multinomial logistic regression model was carried on to determine behavioral attitudes and perceptions towards cycling and bicycle-sharing system of commuters. When compared to private commuters, public bicycle commuters were shown to be 2 times less likely to see bicycle as a speedy, flexible, and enjoyable method of transportation, as well as 2.5 times less likely to perceive benefits. (Curto et al., 2016).

To focus on the commercialized delivery bicyclists, Sarkies and Hemmert (2021) conducted a study to identify whether categorization of cyclists could be done as commercial or non-commercial following medical registers, key demographics and injury characteristics (Sarkies et al., 2021). Usually, commercial delivery bicyclists are encourages to perform delivery quickly (Goods et al., 2019) and delivery distance can range up to 10 km (Maimaiti et al., 2018). This kind of combination does not allow the cyclists to make practical route options to avoid high traffic as a result increasing the possibility of motor vehicle crashes compared to the people cycling for recreational purpose. Moreover, Poor working environments, claims of coercion and manipulation, little training, and dangers faced by commercial cyclists have all been raised as concerns (Lee, 2018). According to Dennerlein and Meeker, 70% messenger bikers miss at least one day of work per year due to injury, where 55% of injured cyclists requiring a medical or hospital appointment (Dennerlein & Meeker, 2002).

Another study from New York stated that almost 35% of all injuries occurred while bicycling for working purpose despite being a mandatory road safety training program in preference of commercial cyclists. The detailed analysis showed that commercial bikers were more likely to be hurt by an open car door in terms of injury mechanism (21.9%) and collide with a taxicab (46.3%). Commercial cyclists were less likely to use electronic devices (5.0%) or drink alcohol (0.7%). Commercial bicyclists were more likely to be hurt by an open car door in terms of injury mechanism (21.9%). Bicyclists on the job were less likely to need surgery (3.9%) (Heyer et al., 2015).

CHAPTER 3: STUDY AREA AND DATA COLLECTION

3.1 Study Area

The survey data was collected from different areas of Dhaka city. The selection of areas were done arbitrarily so that the survey data can be representative and allow to consider variation in perception of commercialized bicycle users of the capital city of Bangladesh.

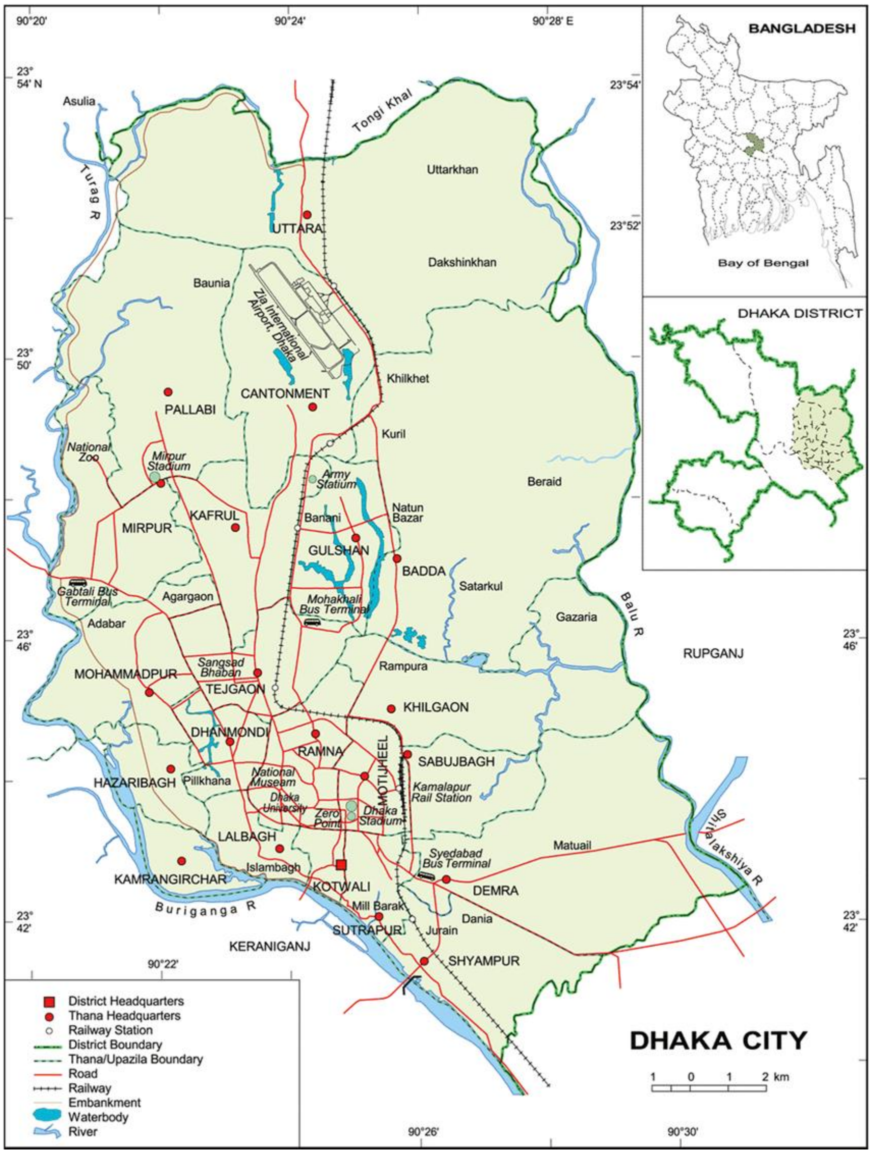


Figure 16: Study area of data collection (Dhaka, Bangladesh)

3.2 Data Collection

A well-prepared questionnaire was designed which was used by the surveyors to interview the general and commercialized bicyclists of Dhaka city. The questionnaire included demographic information, general and commercialized bicyclists' trip information, behavioral perception, behavior towards risky contexts, harassment and preferred policy implications. The questionnaire was generated on the basis of literature review and experts' judgement. Pilot study was done by the survey team to evaluate the effectiveness of the questionnaire as well as the process of conducting the interview.

For this research, all segments of the questionnaire were not considered. To assess the behavioral perception of commercialized bicycle users, demographics, commercialized user trip information and their behavioral perceptions were considered in case of modelling. To satisfy this scope, 751 responses out of 1200 responses were used which specifically are responses of only commercialized bicycle users. The screening process was done by eliminating the partial and irrelevant responses recorded. Figure 17 is given to present the questionnaire pattern prepared and considered variables from that questionnaire.

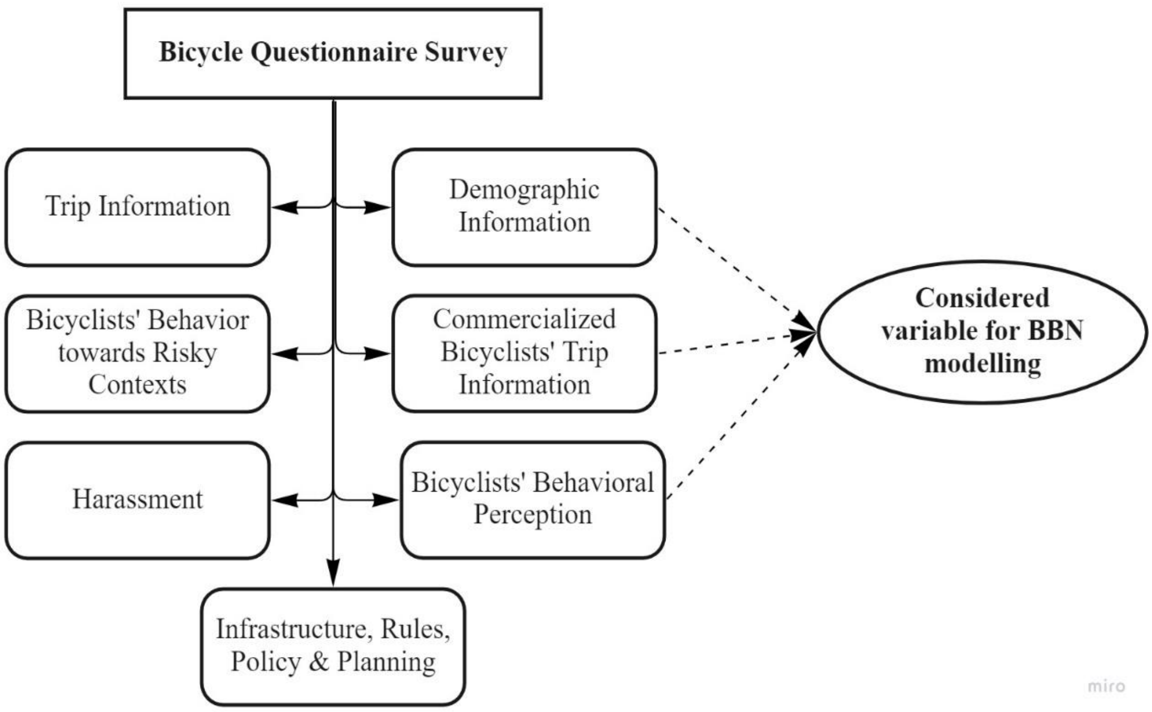


Figure 17: Variables considered in bicycle questionnaire

3.3 Data Processing

In this research, the variables relevant to the scope of the study were extracted from the responses collected based on the well-structured questionnaire. For the ease of model development, some of the scenario specific questions were formed into five major clusters to be more representative of the objective of the research. The clusters were structured focusing for clear representation of the behavioral perception of the commercialized bicycle users. Along with these clustered variables, some variables from demographic and trip information were also considered for model development which did not require further modification. The clusters are presented below in Figure 18.

SI	Clustered Variable	Relevant Scenarios from Questionnaire
1	Accidental Mentality	Not realizing that a parked vehicle intends to leave and consequently having to brake abruptly to avoid collision
		Colliding with parked vehicle which suddenly opens door into the path of an oncoming cyclists
		Colliding with a pedestrian or another cyclist while cycling
		Misjudging a turn and hitting something in road or being close to losing balance or falling
2	Violation of Traffic Rules	Circulating against the traffic (following the wrong way)
		Trying to overtake a vehicle that had previously used its indicators to signal that it was going to turn, consequently having to brake
		Stopping and looking at both sides before crossing a corner or intersection
		Do you apply hand signals while cycling?
3	Personal Traits	Handling or using obstructive objects while riding bicycle (foods, cigarettes)
		Trying to brake but not being able to use the brakes properly due to poor hand positioning
		How often do you get distracted (e.g., while cycling)?
		Bicycling with cognitive pressure
4	Critical Maneuvering	Zigzagging between vehicles while using mixed lane
		Attaining higher speed than required
		Having a dispute in speed or race with another cyclist or driver
		To avoid congestion or save time, have you used bicycle on footpaths?
5	Driving Reaction Quality	Braking very abruptly on a slippery surface
		Failing to be aware of road conditions and falling over a bump or hole
		Circulating under adverse weather conditions

Figure 18: Clustered Variables used in Survey

CHAPTER 4: METHODOLOGY

This chapter presents the methodology followed in this research in a gradual organization. The concern of this study was to identify the causal relationship among features of commercialized bicyclists and perceived behavioral attributes. Because such components are frequently codependent and impacted by prior beliefs, conditional probability can be utilized to demonstrate a causal relationship using the Bayesian Belief Network (BBN). This chapter will provide a brief but comprehensive explanation of the Bayesian Belief Network (BBN) and demonstrate how it might be used to our research.

4.1 Work Flow of the Research

The work flow of the research is outlined below in Figure 19:

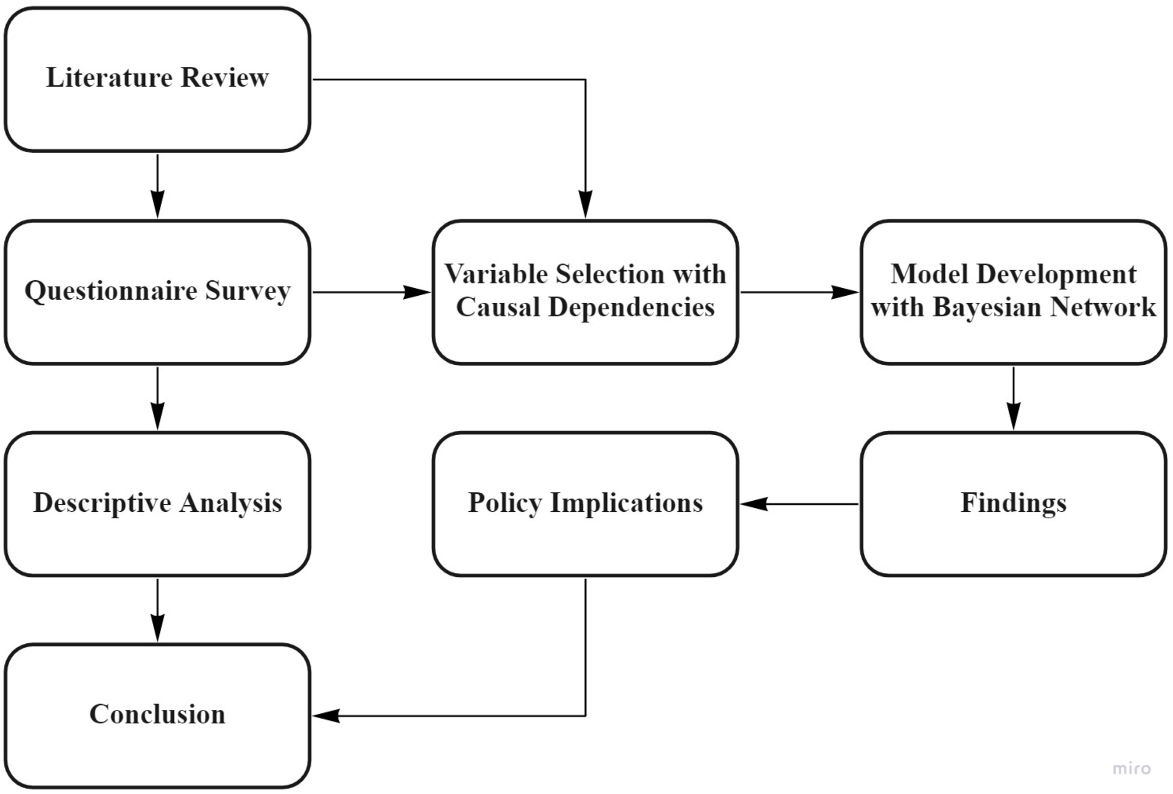


Figure 19: Workflow of the research

The research work started with thorough and extensive literature review. Based on the literatures, the scope of study was identified which was followed in order to prepare well-structured questionnaire. After assessing the efficiency of the questionnaire through pilot study and Focus Group Discussion (FGD), data were collected by conducting field survey. Most relevant variables aligned with research topic were filtered from collected field data, then those filtered data were fitted into Bayesian network in the form of DAG (Directed Acyclic Graph). The model was optimized on the basis of experts' judgement, engineering judgement and knowledge gained from vigorous literature review.

4.2 Bayesian Belief Network (BBN)

In this research, the Bayesian Belief Network (BBN) is implemented to understand the underlying causal relationship between variables such as behavioral perception, demographic characteristics and others reflecting commercialized use of bicycle. Bayesian Networks are also known as recursive graphical models, belief networks, causal probabilistic networks, causal networks and influence diagrams among others (Daly et al., 2011). The causal structure gives a useful, modular insight into the interactions among the variables and allows for prediction of effects of external manipulation. The qualitative expression is represented as a directed acyclic graph (DAG), which consists of a set of variables (expressed by nodes) and their interconnections (denoted by arcs). The probability of the variables are included in the quantitative expression.

A Bayesian Network with three variables, X, Y, and Z, is shown in Figure 20. X and Y are the parents of variable Z, indicating that Z is the dependent node. Z's probability is a conditional probability based on X and Y's probabilities. The probabilities in a Bayesian Network are simplified by the DAG structure of the BBN, by applying directional separation (d-separation) (PEARL, 1990) and a Markov property assumption (Jensen & Nielsen, 2011; Johnson et al., 2010), so that any variable's probability distribution is exclusively dependent on its parents. The Bayesian framework is based on the Bayes hypothesis also known as the Bayes rule (Wang & Vassileva, 2005). Thus, the probability distribution in a BBN with n nodes ($X_1, . . . , X_n$) can be formulated as

$$P(X_1,\ldots\ldots, X_n) = \prod_{i=1}^{n} P(Xi \mid Pa\ (Xi))$$

where Pa(Xi) is the set of probability distributions equivalent to the parents of node Xi (Heckerman et al., 1995; Johnson et al., 2010). For Figure 20, the above equation can be written as,

$$P(Z) = P(Z \mid X, Y) * P(X) * P(Y)$$

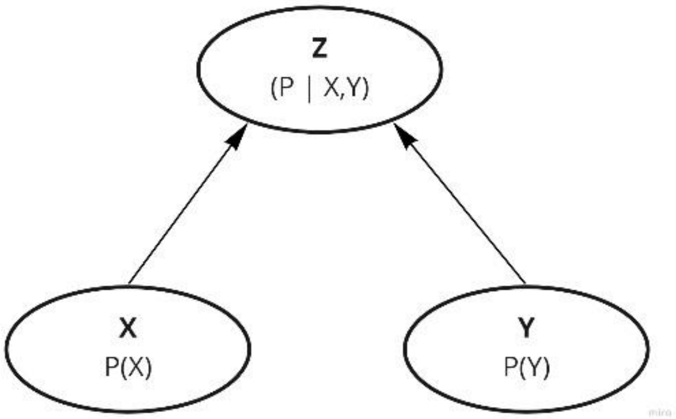


Figure 20: Representation of Bayesian network

In Bayesian structure, over-parameterization is not a concern as BBN focus on interdependencies and pattern of powerful linkages. To understand the complete data structure, three ways are usually used to build Bayesian network. Those are, (i) modeling based on expert knowledge; (ii) obtaining from database learning. (iii) creating from a knowledge base (Ma et al., 2020). Expert knowledge, measurements, and objective frequency data can all be used to create the structure and numerical probability.

In this study, the mixture method was adopted for network building. The data obtained from the questionnaire was imported into GeNIe 3.0 Academic Version and the structural learning was completed using Peter-Clark (PC) algorithm. PC algorithm is a popular constraint-based method used for causaldiscovery and also allows for continuous data. This algorithm employs Conditional Independence (CI) test between pairs of variables to develop the structure of the network (Tsagris, 2019b).

4.3 GeNIe Workspace

GeNIe (Graphical Network Interface) is a software tool developed for decision analysis and graphical illustration of the union of probability and network occurrences. GeNIe can be used for analysis of Bayesian networks. The calculation of a Bayesian network with huge number of inter-connectednodes can get very complex at times and GeNIe can easily handle the analysis of such type of problems in presence of noisy data and uncertainty measure.

GeNIe 3.0 Academic Version was used for structural learning (network building) and parameter learning (preparation of CPT). GeNIe offers various analysis choices after parameter learning is complete, such as observing prior and posterior marginal probability, sensitivity analysis, tornedo diagram, degree of influence, and so on.

CHAPTER 5: ANALYSIS AND RESULT

This chapter presents the main findings of the study after completing data analysis using BBN model. The data collected from the survey was re-categorized and re-distributed initially based on descriptive statistics. The fine-tuned data was then fit into Bayesian network structure. The nodes of the network were modified and tested to understand each variable's impact on selected target variable. Several analysis works were carriedout on the model such as- sensitivity analysis, tornedo diagram. The accuracy of the model was also tested using the built-in model validation feature of the GeNIe software. After the completion of analysis step, all the findings of the research were aggregated and presented in this chapter concisely.

5.1 Descriptive Statistics and Analysis

The scenarios representing the behavioral perception of the commercialized bicyclists were recorded in Likert Scale. To assess the impact of those scenarios, the whole Likert scale was converted into scoring system. For scoring, the frequency was set following the study on validation of Cycling Behavior Questionnaire (CBQ). The 5-level frequency based response scale was: 0 = never; 1 = rarely; 2 = often; 3 = more often; 4 = always. (Useche et al., 2018). After scoring all the scenarios, the total score for each clusters were classified (based on quartile range) into three corresponding groups based on total score of each cluster. The three groups were generalized centering the attitude of commercialized bicyclists as- high propensity, moderate propensity and low propensity in attributes.

Other than behavioral variables, use of safety gears were also reclassified in accordance with scoring system (out of 44). Thus, were regrouped into two categories (based on quartile range) – frequent use (3-20) and seldom use (21-44).

Relevant descriptive statistics of essential variables in terms of behavioral perception (Accidental mentality, Violation of traffic rules, Critical maneuvering, Personal traits and Driving reaction quality) are presented in the table below:

Table 4: Descriptive Statistics of variables in terms of behavioral perceptions (Accidental Mentality, Violation of Traffic Rules, Critical Maneuvering, Personal Traits and Driving Reaction Quality)

Variables	Low Propensity (n =1182)		Moderate Propensity (n=1810)		High Propensity (n=783)	
	No.	%	No.	%	No.	%
Age						
<18	70	5.92	156	8.62	114	14.94
18-25	550	46.53	1002	55.36	443	58.06
25-35	490	41.46	574	31.71	161	21.10
>35	72	6.09	78	4.31	45	5.90
Gender						
Male	863	99.20	1532	99.20	565	97.92
Female	7	0.80	25	1.61	12	2.08
Monthly Income						
5-10k	103	8.71	324	17.90	333	43.64
10-15k	457	38.66	674	37.24	149	19.53
15-20k	535	45.26	648	35.80	162	21.23
>20k	87	7.36	164	9.06	119	15.60
Profession						
Private Employee	878	74.28	1008	55.69	104	13.63
Student	140	11.84	417	23.04	393	51.51
Delivery Person	86	7.28	144	7.96	125	16.38
Garment Worker	32	2.71	1166	6.41	67	8.78
Others	46	3.89	125	6.91	74	9.70
Ownership Type						
Personal	1042	88.16	1489	82.27	579	75.88
Company provided	131	11.08	296	16.35	158	20.71
Rental	9	0.76	25	1.38	26	3.41
Consecutive Shift						
< 3 hours	173	14.64	315	17.40	157	20.58
3-6 hours	620	52.45	1054	58.23	536	70.25
6-9 hours	389	32.91	441	24.36	70	9.17
Safety gears used						
Frequently	828	70.05	1265	69.89	502	65.79
Seldom	354	29.95	545	30.11	261	34.21
Accessories used						
1	282	23.86	258	14.25	85	11.14
2	680	57.53	1162	64.20	453	59.37
3	150	12.69	277	15.30	168	22.02
>3	70	5.92	113	6.24	57	7.47

5.2 Model Development and Analysis

The preliminary Bayesian network structure of behavioral perception of commercialized bicyclists was developed using PC algorithm. PC algorithm is one of the most popular structural learning algorithm which uses independencies observed in dataset for reasoning of the network. After forming the DAGs, the optimal network structure were formed in reference with expert knowledge and engineering judgement.

For parameter learning, built-in Expectation-Maximization (EM) algorithm was used in GeNIe. This process allowed to get the joint probabilistic reasoning of the network. The marginal probability is known to be the summation of cluster of variables in accordance with specific target variables (Ma et al., 2020). Thus, the marginal probabilities of parent nodes were obtained from joint probability distribution.

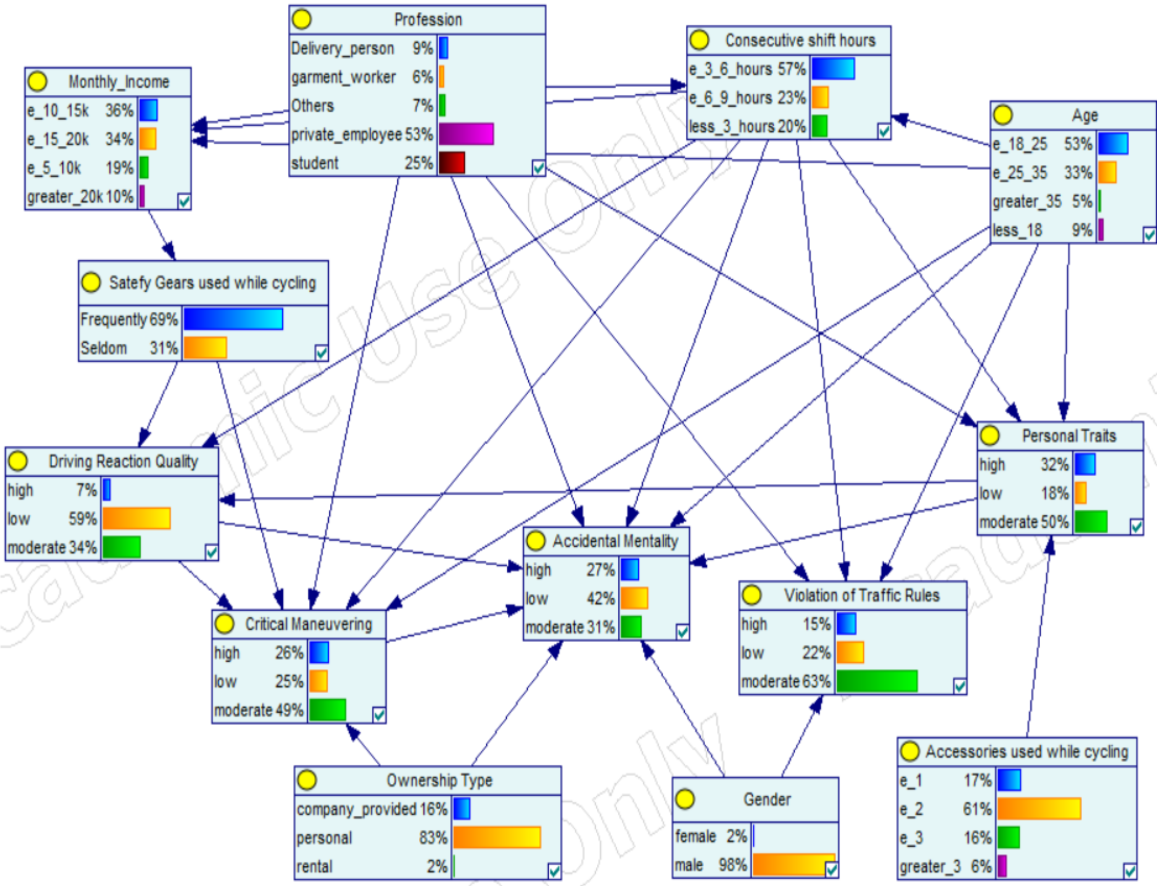


Figure 21: Prior Marginal Probability Distribution Diagram of 'Behavioral perception of commercialized cyclists'

According to this Bayesian structure, the prior marginal probabilities of each node can be explained. Age, profession, ownership type, gender, consecutive shift hours, driving reaction quality, critical maneuvering and personal traits have a direct influence on accidental mentality. Consecutive shift hours act as parent node of monthly income, driving reaction quality, critical maneuvering, accidental mentality, violation of traffic rules and personal traits as well as child node of age and profession. Moreover, ownership type remains as parent node of critical maneuvering and accidental mentality whereas gender remains as parent node of accidental mentality and violation of traffic rules. Also, use of safety gears acts as parent node of driving reaction quality and critical maneuvering while acts as child node of monthly income. On the contrary, some variables have indirect influence on behavioral attributes. Such as – monthly income is neither parent node nor child node of any behavioral attributes but have direct influence on use of safety gears that can have indirect impact on other behavioral perceptions.

5.3 Model Validation

Model functionality representation was evaluated using the default validation tool provided in GeNIe expressed in terms of Receiver Operating Characteristics (ROC) curve. The simplest validation ‘Test only’ was used in the process as this is more suitable for the models those has been developed based on expert judgement. This validation process amounts to testing the model on the data file. The ROC curve shows multiple cut points and their corresponding sensitivity vs. 1-specificity graphically (i.e., false positive rate). Thus, ROC curve allows identifying the theoretical limits of accuracy along with the most suitable criterion for the application available. The baseline ROC curve determines the prediction accuracy limit and this accuracy is quantified with the representation of area under the ROC curve (AUC). The AUC above the baseline reflects a good model fit and value closer to 1 suggests better performance of the model (Park et al., 2004). Generally, AUC value equal or above 0.7 is observed to be an acceptable limit for validation.

In this study, in order to predict behavioral perception model, accidental mentality and violation of traffic rules are considered as class nodes. AUC values for high propensity, moderate propensity and low propensity towards behavioral attributes of accidental mentality obtained from ROC curves are 0.98, 0.89 and 0.93 respectively. In addition, AUC values for high propensity, moderate propensity and low propensity towards behavioral attribute of violation of traffic rules obtained from ROC curves are 0.71, 0.71 and 0.73 respectively. All the values portrays the model to be good enough.

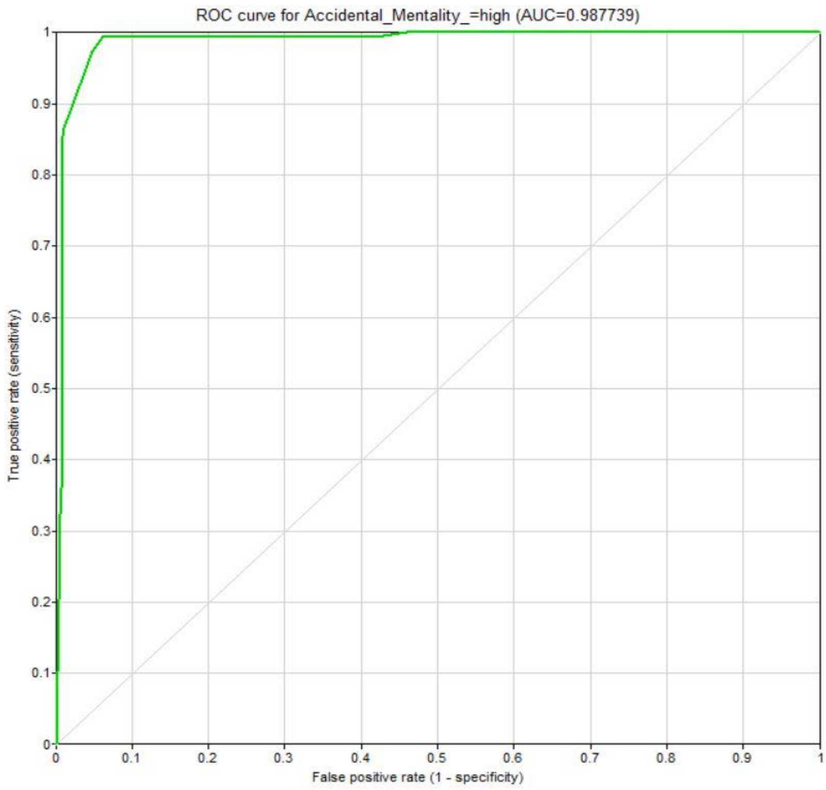


Figure 23: ROC curve for high Accidental Mentality

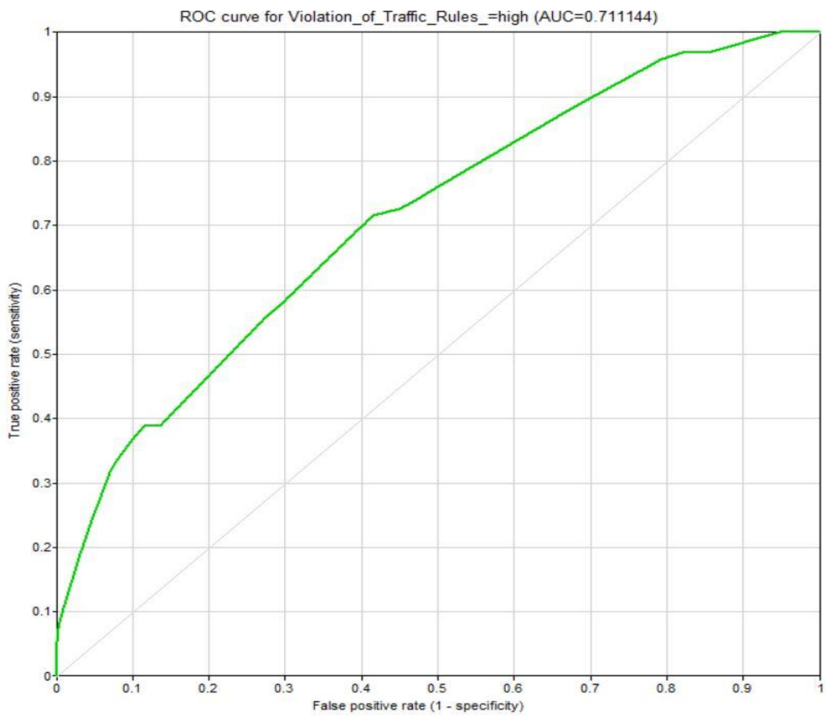
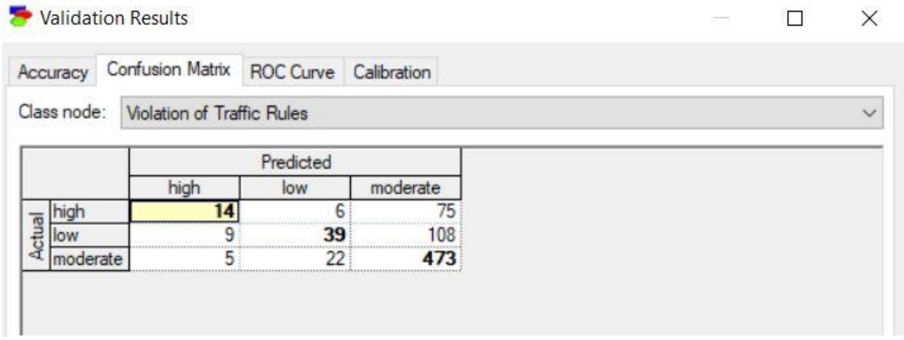


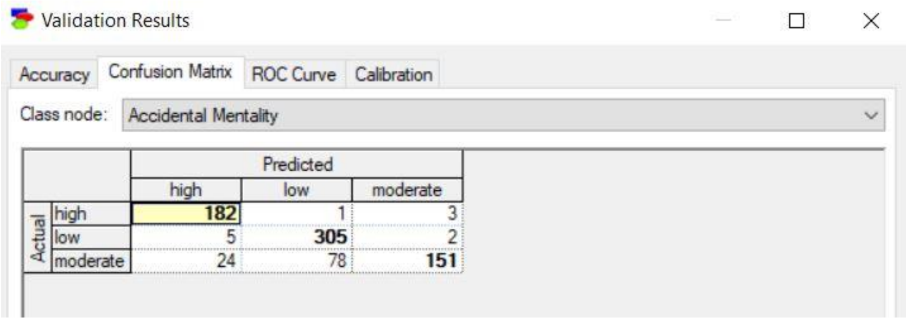
Figure 22: ROC curve for high Violation of Traffic Rules

Confusion matrix layout is also a visual representation of model performance. In the confusion matrix, column represents actual state whereas row represents model prediction state. The bold diagonal of the confusion matrix shows the numbers of correctly identified class whereas off-diagonal shows incorrectly identified class. The confusion matrix for behavioral attributes are attached here-



Actual \ Predicted	high	low	moderate
high	**14**	6	75
low	9	**39**	108
moderate	5	22	**473**

Figure 24: Confusion matric of Violation of Traffic Rules



Actual \ Predicted	high	low	moderate
high	**182**	1	3
low	5	**305**	2
moderate	24	78	**151**

Figure 25: Confusion matrix of Accidental Mentality

5.4 Model Output and Explanation

Commercialized bicyclists with higher tendency of comprehending towards negative behavioral attributes put under ‘High’ and similarly moderate competency as ‘Moderate’ and low tendency as ‘Low’. Figure **21** shows the prior marginal probabilities of each node whereas Figure **26** shows the posterior marginal probabilities when the target variable’s state ‘High’ is set as evidence. Similarly, Figure **27** and Figure **28** shows the posterior marginal probabilities when ‘Moderate’ and ‘Low’ is set as evidence in the target variable respectively.

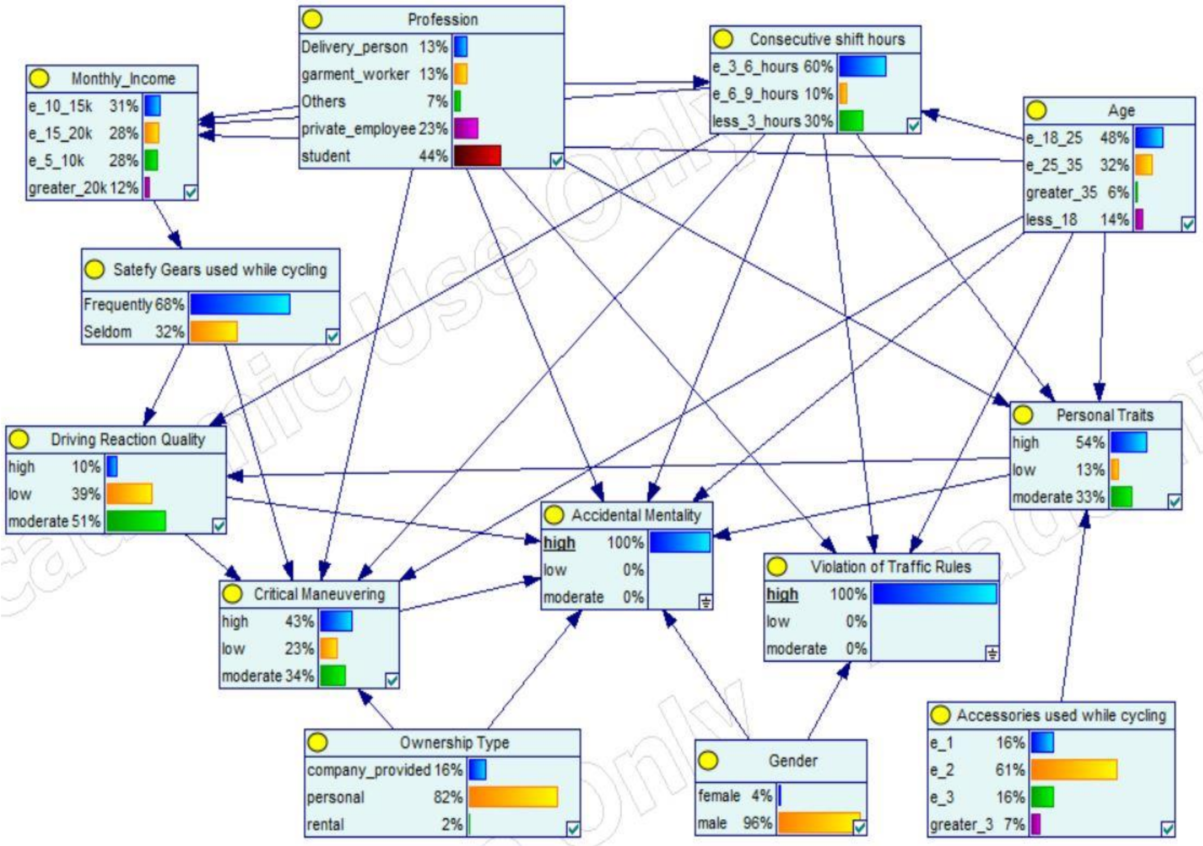


Figure 26: Posterior marginal probability distribution diagram when target variables are set 'High' as 100%

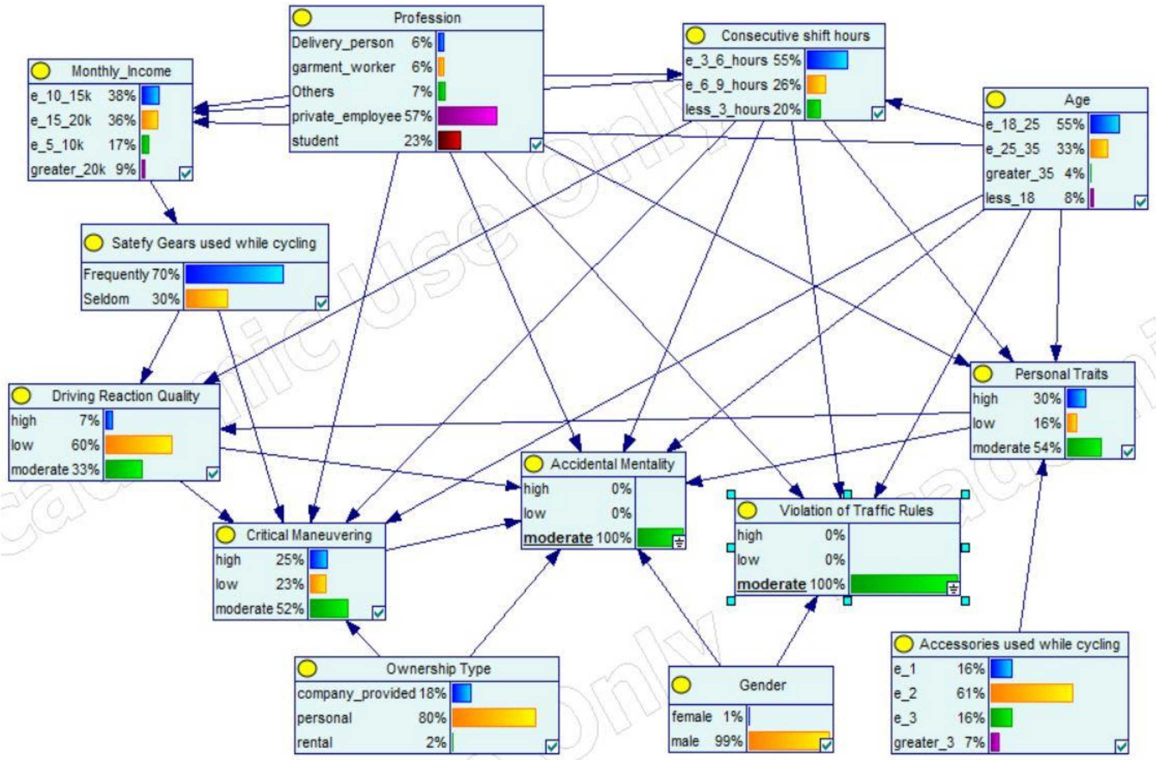


Figure 27: Posterior marginal probability distribution when target variables are set 'Moderate' as 100%

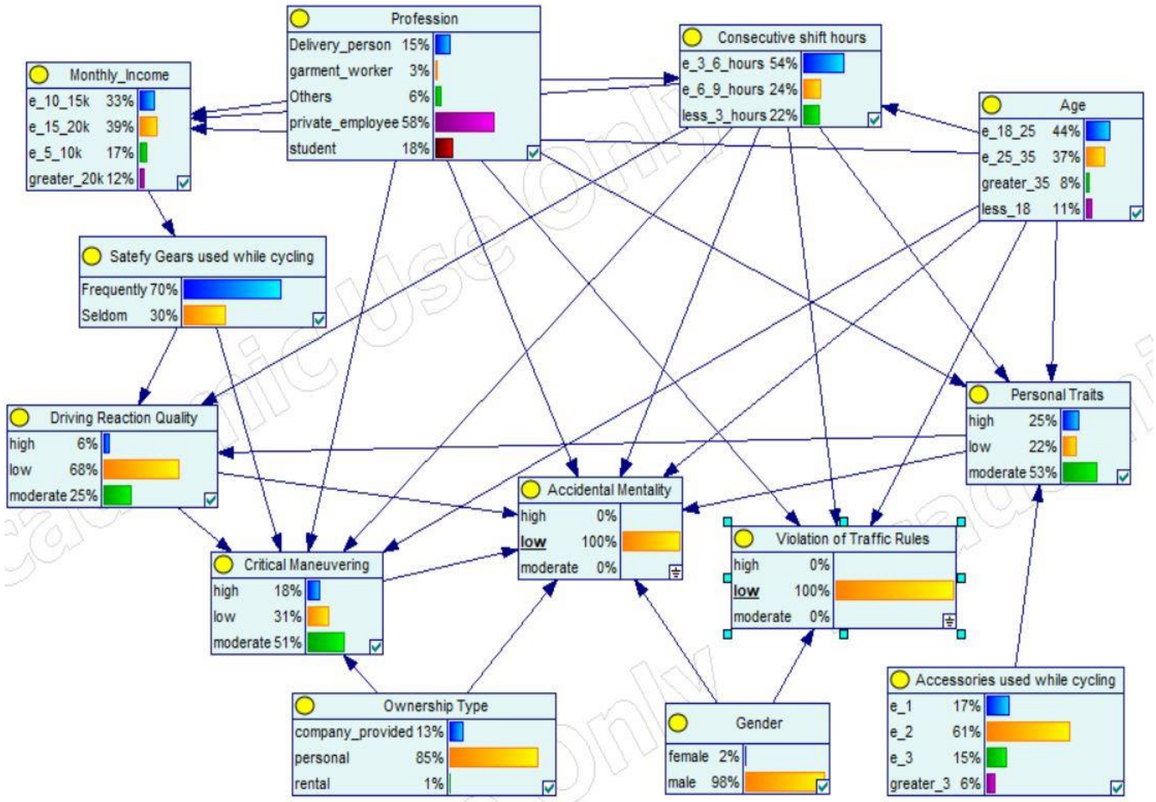


Figure 28: Posterior marginal probability distribution when target variables are set 'Low' as 100%

The posterior marginal probabilities of each node were observed for all the evidence of target variable ‘Accidental Mentality’ and ‘Violation of Traffic Rules’. Table **6** illustrates the outcomes of the observation.

Table 5: All nodes marginal probabilities for ‘High’, ‘Moderate’ and ‘Low’ state of target variables ‘Presence of Accidental Mentality & Violation of Traffic Rules’

Attribute	Attribute Category	Evidence (%) Accidental Mentality & Violation of Traffic Rules		
		High	Moderate	Low
Gender	Male	96	99	98
	Female	4	1	2
Age	<18	14	8	11
	18-25	48	55	44
	25-35	32	33	37
	>35	6	4	8
Profession	Student	44	23	18
	Private Employee	23	57	58
	Delivery Person	13	6	15
	Garment worker	13	6	3
	Others	7	7	6
Monthly Income	5-10k	28	17	17
	10-15k	31	38	33
	15-20k	28	36	39
	>20k	12	9	12
Bicycle Ownership Type	Personal	82	80	85
	Company Provided	16	18	13
	Rental	2	2	1
Consecutive Shift Hours	< 3 hours	30	20	22
	3-6 hours	60	55	54
	6-9 hours	10	26	24
Accessories used while cycling	1	16	16	17
	2	61	61	61
	3	16	16	15
	> 3	7	7	6
Safety Gears used while cycling	Frequently	68	70	70
	Seldom	32	30	30
Critical Maneuvering	High	43	25	18
	Moderate	34	52	51
	Low	23	23	31
Personal Traits	High	54	30	25
	Moderate	33	54	53
	Low	13	16	22
Driving Reaction Quality	High	10	7	6
	Moderate	51	33	25
	Low	39	60	68

The analysis shows that when the evidence is set from ‘low propensity’ to ‘high propensity’, the tendency of critical maneuvering increases from 18% to 43% whereas driving reaction quality drops from 68% to 39%. The high propensity of accidental mentality and violation of traffic rules are governed the students (44%) whereas private employee (58%) governs low propensity of those two attributes. The age group of 18-25 were dominant in all evidence sets followed by age group of 25-35 years. Consecutive shift hours of the commercialized cyclists influences the behavioral norms actively. Majority of the cyclists who works for 3-6 hours for commercial purpose shows constant tendency of perceiving negative behavioral attitudes. If the difference in propensity is considered, then steadily working for 6-9 hours increases risky tendency by 14% when the evidences are set as high to low.

5.4.1 Sensitivity Analysis

To gain better understanding of the most important variables, sensitivity analysis was performed on the existing network. GeNIe displays the effect of variation in the target variable in a sensitivity study. The dark red variables have the most influence on the target variable. The impact gradually reduces as the red color intensity lowers. White variables have minimal impact on the target variable, while grey variables have no impact at all.

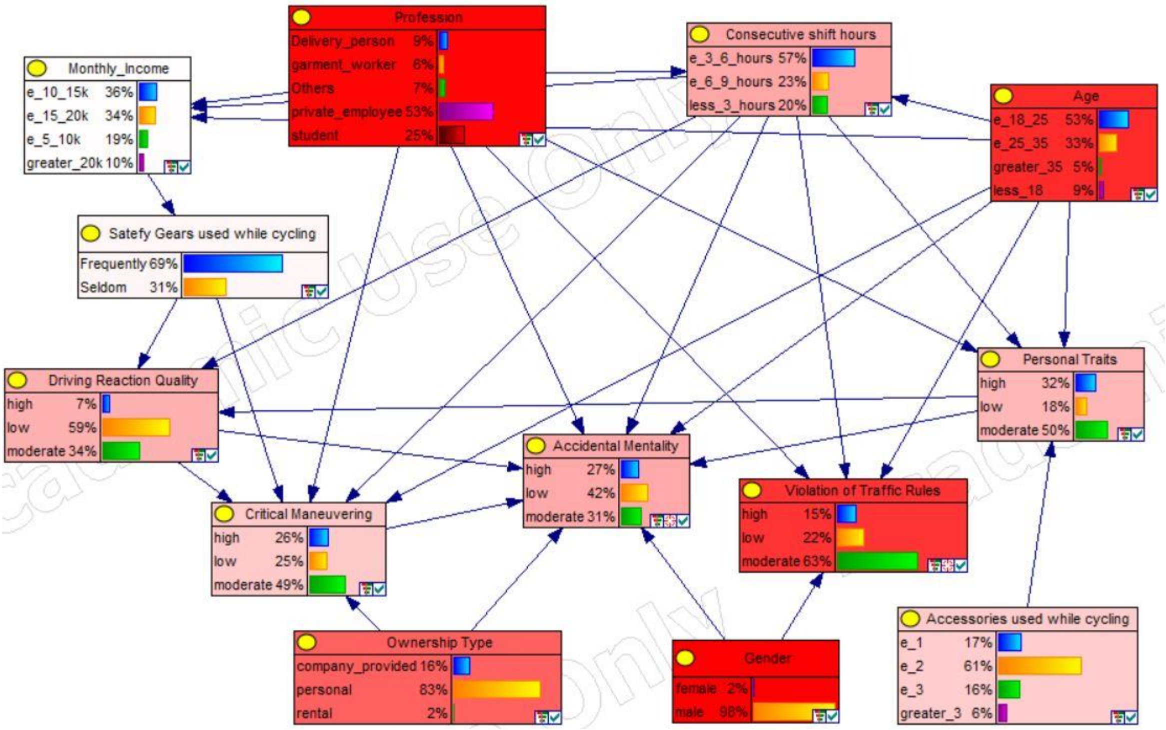


Figure 29: Sensitivity Analysis of 'Behavior Perception Model for Commercialized Bicyclists'

‘Accidental Mentality’ and ‘Violation of Traffic Rules’ are specified as the target variables in the sensitivity analysis. The sensitivity analysis shows that the most significant variables are ‘Age’, ‘Gender’ and ‘Profession’. ‘Ownership Type’ was found to be the second most important whereas ‘Consecutive shift hours’, ‘Personal Traits’ and ‘Driving Reaction Quality’ were the third most influential variables on the target. ‘Critical Maneuvering’, ‘Safety gears used’ and ‘Accessories used’ have the minimum influence on the targeted behavioral attributes. It was also found that monthly income of the bicyclists does not impact the accidental mentality and tendency to violate traffic rules at all.

A tornado diagram in sensitivity analysis identifies the most significant state of a variable for a selected state of the target variable. For the behavior model, profession was found to be most significant on high propensity of accidental mentality whereas, the result also dictates higher helmet prevalence among riders who avoid wearing helmet ‘never’ or ‘sometimes’.

Figure 30: Tornado diagram in sensitivity analysis when Accidental Mentality is 'High'

Figure 31: Tornado diagram in sensitivity analysis when Violation of Traffic Rules is 'High'

CHAPTER 6: CONCLUSION AND RECOMMENDATION

This chapter incorporates the major findings of this study and credible recommendations formulated from model outcomes. The recommendations and implications might be reasonable for policy makers, transport planners, vehicle users and all other relevant personnel to progress with sustainable transport development. The limitations and future scopes of our investigation were features in the final remark.

6.1 Key Findings

The developed Bayesian model allowed to identify the key factors which are influencing the behavior of commercial bicyclists and those significant variables are mainly the considered demographic variables. Age is one of the most significant variable and the dominant age group is the younger adults of 18-25 years (53%) followed by age group of 25-35 years (33%). Accidental mentality and violation of traffic rules tendency of commercialized bicyclist increases steadily in case of each age group. Moreover, students are having increasing tendency of behavioral attributes whereas contrasting scenario is seen in case of private employee as they show decreasing tendency of perceiving risky mentality. This portrays that the students are more involved in commercial purpose using bicycle and as a result found to be more vulnerable.

Ownership type, consecutive shift hours and use of safety gears while cycling are some specific attributes featuring commercialized characteristics. Typically, the more working hours impair riding decision as creates fatigue consequently. The analysis showed that tendency of perceiving behavioral attributes of accidental mentality and violation of traffic rules decreases by 14% in higher shift hours of 6-9 hours. This disparity can happen due to the fact that the bicyclists are professional enough or trained as they regularly cycle to serve commercial purpose. Study of developed countries show that frequency of the use of the safety gears does not influence the behavioral change of cyclists (Vanparijs et al., 2015). The model analysis aligns with the study as use of safety gears (helmet, reflector, light color clothing, rear view mirror, etc.). From the study, ownership type creates distinction in behavioral approach significantly and observed that people tends to show higher tendency of risky attitudes while riding personal bicycle 83% which is quite higher than riding company provided bicycle (16%).

Other general attributes of critical maneuvering, influence of surrounding road and weather condition and personal characteristics moderately effects the overall model. Critical maneuvering of commercialized bicyclists on road with other traffic flow shows 25% shift with increasing tendency of perceiving both the accidental mentality and violation of rules. In case of higher tendency in perceiving personal traits while cycling shows 29% transfer with increasing likelihood in perceiving both the target variables whereas higher tendency in perceiving effect of surrounding road and weather condition while cycling signifies 29% shift with decreasing likelihood in perceiving the targeted behavioral attributes. In the model, gender acts as significant variable but here the male to female percentage seems to be biased. Considering all other significant variables with valid reasoning, gender does not affect the distinction of the developed model.

6.2 Recommendation and Policy Implication

This study aimed to unveil the obvious effects of factors on the behavioral perception of commercialized bicyclists from thestandpoint of a developing country. For this purpose, a survey was conducted in different areas of Dhaka city highlighting the socio- demographic and behavior perception-related information. Specific portion of the questionnaire was designed to assimilate the real expectations of the surveyed bicyclist population regarding infrastructure and policy implications. This portrayed that 94.54% of the commercialized bicyclists prefer lane provision for bicycle movement whereas 30.91% desired for on-road shared bicycle boulevards, around 21% for separate bicycle lane and protected bicycle lane and 12.46% for painted on sidewalk. Moreover, most preferred design elements by commercial cyclist was provision of proper signs and pavement markings and nearly 27% emphasizes the most for interference of government by implementation of low speed neighborhood as well as public bicycle sharing scheme to ensure bicycling. Also, 73% of the commercialized insists that separate planning should be done for different area based bicycle users as characteristics differ significantly.

On the contrary, the collected data on commercialized bicyclists were fit intoa Bayesian network and through rigorous analysis, significant indicators such as age, profession, presence of safety gears; critical maneuvering characteristics and ownership type were identified. The findings of the research were able to shed light on aspects that are to be brought under government policy to achieve safe and sustainable situations in favor of the commercialized cyclists. Extensive international research has recommended improved active transportation infrastructure and road design, including integrated, connected, and convenient amenities with physical parting from motor vehicles (Lusk et al., 2011; Teschke et al., 2012). Although traffic education for road users may help enhance safety, no high-quality data was found that may minimize collision-related injuries among commercial delivery cyclists, especially when their cycling behavior is assumed to be influenced by competition for delivery speed (Zhuo Wanga, Richard L. Neitzel, Wenlong Zheng, Dezheng Wang, 2021).

6.3 Limitation and Future Scope

This research can be considered novel as this study identified factors that affect behavioral perceptions of particularly commercialized bicyclists, which has not been addressed by researchers locally. Besides, a causal relationship among the identified factors was established from which affect of one variable to another can be observed very easily. However, thereare still some limitations in this study which require addressing.

The major limitation of the study was survey location. The picked locations of the survey were at areas of Dhaka city only. To achieve more representative data, study area can be extended to rural areas and other cities in future. There is a noticeable biasness in gender perception due to lack of data of female bicycle users.

SECTION 3: ROAD USERS' PERCEPTIONS OF SAFETY IN CONTEXT OF NON-MOTORIZED VEHICLE MOVEMENT

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

The advancement of transportation systems and vehicles had a great influence on the development of human civilization. The whole spectrum of transportation vehicles can be put into two major categories which are the MVs or the Motorized Vehicles and the NMVs or the Non-motorized vehicles. But along with the development of the transportation system, the issue of traffic accidents has also become a burden for mankind since 1.35 million people are killed annually in traffic accidents, with vulnerable road users accounting for more than half of all road traffic fatalities(WHO, 2018). As NMVs are also considered to be in this vulnerable road users (VRUs) group (Hoque et al., 2008; Meena et al., 2014), ensuring their safety has become a major demand of modern times.

The modal composition of Asian cities varies greatly. In many parts of Asia, NMVS or non-motorized vehicles (NMVs) such as cycle-rickshaws, bicycles and carts are now common modes of transportation. In many Asian cities, NMVs account for 25 to 80 percent of vehicle journeys, more than anyplace else on the planet (Replogle, n.d.). The concept of NMVs is not generalized and examples vary significantly from country to country, especially in African and Asian regions where they are predominant and most often act as intermediate public transports (Kumar et al., 2016). In many Asian cities, bicycles are the most common mode of NMVs. Bicycle ownership in Asia has surpassed 400 million and is steadily increasing. While bicycle is the most common example of a non-motorized vehicle, cycle-rickshaws, bullock carts, cycle-vans, etc. are also major examples of NMVs in countries like India and Bangladesh. This region is home to the majority of the world's 3.3 million cycle rickshaws and goods tricycles. Despite repeated efforts by some local governments to ban cycle rickshaws in favor of motorized cars, the number and use of these vehicles is expanding in many regions in response to otherwise unmet transportation demands. Becaks, also known as cycle-rickshaws or pedicabs, play an even larger part in urban mobility in a number of Indonesian cities than bicycles. In Bandung in 1985, cycle-rickshaws accounted for 12% of all work trips and an even higher percentage of non-work excursions, while bicycles accounted for about 6% of trips. In 1985, cycle-rickshaws (becaks) accounted for 4.6 percent of all journeys in Jakarta, where the government is aggressively repressing them through bans and confiscations, while bicycles accounted for only 2.4 percent. (Replogle, n.d.). Our study on NMVs safety will encompass modes like cycle rickshaws and vans in Dhaka, Bangladesh.

Dhaka, Bangladesh's capital and largest metropolis, with a population of almost 12 million people. The city is known as a rickshaw capital. Urban areas like Dhaka account for more than three-quarters of Bangladesh's cycle rickshaws. Each year, these urban cycle rickshaws transport over 30,000 passengers and approximately 100 tons of commodities. In the transportation business, bicycles, rickshaws, bullock carts, and country boats account for about 75% of value contributed, 80% of employment, and over 40% of vehicle assets. Non-motorized transport vehicles account for around 85% of traffic on minor roads. Dhaka's rickshaws transport more passengers per day than the London Underground (Efroymson & Bari, 2005). Each day, about 400,000 rickshaws serve as one of Dhaka's primary sources of transportation(Hossain & Susilo, 2011). And the reason is easily understandable as they provide a cheap mode of transportation for the city's huge number of residents with adjustable fares and the ability to reach practically any location in the metropolis. Short-distance travel is great for them. While they are prohibited on many major roads, they are ideal for navigating tight alleys and reaching destinations in congested areas of the city (*Dhaka's Cycle Rickshaws – Lifeblood of the City — XyzAsia*, n.d.).

Despite their importance in urban environments, most of these non-motorized three-wheelers have been associated with unfavorable attitudes because of their contributions to traffic congestion, and involvement in fatal crashes (Jayatilleke et al., 2015). Every day, approximately eight people are killed in road accidents in Bangladesh. Because of their light and delicate build and huge speed differential with their motorized equivalents, NMV pullers and users are regarded the most vulnerable category to road traffic accidents. NMVs were involved in about 11% of all accidents (Ahsan & Sufian, 2014). Approximately 800 deaths were linked to cycle rickshaws and bicycles in urban areas of Bangladesh between 1998 and 2006, accounting for roughly 12% of total urban traffic deaths. The most common types of cycle rickshaw accidents are rear end (70%) and head on (15%), demonstrating a severe problem of being hit from behind in traffic(Hoque et al., 2008). Reasons for high casualty rates related to NMV accident (almost 50 percent) may include heterogenous traffic systems prevalent in the urban cities e.g., Dhaka, unsafe vehicle structure and unsafe vehicle dynamics that puts this category of vehicle at risk of high impact collision with motorized vehicles. Low-mass vehicles are not often intended to resist collisions (Egertz et al., 2011). Even at moderate crash speeds, low-mass three-wheelers have limited crashworthiness and a high risk of severe injury, according to one study (Schmucker et al., 2011). Due to its unstable and flimsy frame, exposed sides, and lack of safety equipment such as seat belts and airbags, three-wheelers are considered dangerous. One of the disadvantages of three-wheelers is their poor roll-over stability, which makes them vulnerable to road accidents (Priye & Manoj, 2020).

The majority of scientific study on road traffic crashes that been conducted in developed countries included car-occupants. However, there is a scarcity of study on the safety of small low-mass vehicles, notably three-wheelers like cycle rickshaws (Chawla et al., n.d.). Most of the studies in Bangladesh were performed on behavioral perspectives. In Rajshahi & Khulna, the congested areas were considered to categorize the incentives and deterrents to NMVs, interviewing, and analyzing various user perspectives (Md. Raihan Gafur, 2017; Sahriar et al., 2020). Besides behavioral research, some investigations were carried out utilizing other modeling methodologies. The impacts of reducing non-motorized vehicles in urban corridors of Dhaka were studied using a micro-simulation model (Hossain & Mcdonald, 1998). The multinomial logit model was integrated into determining the preferences and concerns of NMV users and non-user, whereas it also evaluated the probability and perceptions of mode choice (Haroon et al., n.d.).

Various research has been undertaken around the world to discover the variables that affect safety directly or indirectly. However, such factors are not necessarily mutually independent, and it is more commonly the combined influence of many factors that influences one's opinion regarding safety of the NMVs plying on our roads. As a result, the causal relationship between such components should be investigated in order to have a better understanding on road user’s perspectives regarding the matter. Due to the combined influence of factors such as any prior history with road accidents, driving location, and road conditions, perceptions regarding NMV safety may differ from person to person. Because casual associations are built on previous beliefs, conditional probability can be used to construct a relationship between the variables using Bayesian theory. Compared to traditional regression analysis and parametric tests, Bayesian Belief Network or BBN can self-assemble, identifying the best connection arrangement to explain the target variable. They comprehend data structures and look for the strongest links. Because variables are connected in a network, they all influence one another—a change in one affects the others. Furthermore, because the BBN looks at interdependencies—patterns of links and effects—adding additional variables has less of an influence. When more factors are added, the ones that have the greatest impact, based on their distributions, continue to have those effects. The BBN has no problems with over-parameterization (Quddus & Hossain, 2021).

1.2 Purpose and Objective

Identification of the factors that have a greater influence on road users' safety perception on NMV movements can be valuable information for policymakers and transportation corporations to implement and execute measures that promote safety improvements regarding NMV movements. Thus, our study attempts to determine the key factors influencing the aforementioned safety perceptions in national and regional highways of a developing country e.g., Bangladesh.

The key objectives of our study are:

- Identify key factors influencing a road users' perspective on safety regarding non-motorized vehicle movement.
- Investigate variations in safety perceptions across different socio-demographic segments.
- Recommend relevant policies and assist in the development of tailored interventions from the perspective of a developing country.

1.3 Scope of the study

The goal of the study is to identify crucial variables that affect road users' safety perceptions and to establish a causal relationship between those elements. During the survey phase of this study, respondents and focus group participants came from various parts of the city. The survey participants' variety ensured the most representative response.

1.4 Organization of the thesis

The whole thesis work has been divided into five chapters and the brief descriptions of the chapters are presented below:

Chapter 1 (Introduction): This chapter presents the background, the problem statement, purpose, and objective along with the scope of the research.

Chapter 2 (Literature Review): This chapter addresses the pertinent pieces of literature that aided in the development of the most appropriate research work plan.

Chapter 3 (Methodology and data collection): Scoping, bounding, and data acquisition procedures are discussed in this chapter along with the research's gradual working process and displays the approach used to examine the data.

Chapter 4 (Analysis and Results): This chapter discusses the analysis of collected data and interpretation of the results obtained.

Chapter 5 (Conclusions and Recommendations): This chapter summarizes the research's principal findings and suggests policy implications.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The direct effect of safety variables is on the users' mode choice decisions (Ari Suryanto et al., 2019). Thus, we start our discussion with the summary of existing literatures conducted regionally and internationally on the factors affecting non-motorized mode choice, followed by non-motorized safety along with their methodology and final results is discussed in detail. We conclude by a summary on the available literatures on NMV safety in context of Bangladesh.

2.2 Previous studies on non-motorized mode choice

In order to anticipate how various built environment (BE), and other usual demographic factors influence non-motorized travel choices, various models were developed using data taken from household travel survey in Seattle, Washington. Factors like- street connectivity, higher bus stop density, greater NMT access influenced higher rates of NMT trip generation per day and among the BE variables, street structure showed the greatest impacts(Khan et al., 2014). When a similar sort of study was conducted in a 3-mile buffer of a university area, Lundberg & Weber (2014) highlighted that increases in connectivity, accessibility, and proximity to non-motorized facilities, and decreases in commute distance and cars per house all had positive effects on non-motorized travels. An intriguing discovery revealed that a person's good view of non-motorized networks is linked to their travel behavior, and that this understanding diminishes as commuting distance to school increases.

In countries of the Asian subcontinent, the scenario differs a bit. A study using multinomial logit analysis, aimed to provide empirical evidence about the relation between built environment and mode choice in context of Indian city of Rajkot. Results showed land use mixing and balance helps in encouraging non-motorized and public transport modes, while access to destination, commute distance has strong influence on walk mode choice, however very little influence on bicycle and rickshaw choice (Munshi, 2016). Existence of "Second gender effect” in mode choice of this subcontinent was shown by Singh & Vasudevan (2018), which found that girls were less likely to use non-motorized modes for traveling to school. It is a proof that in a gender-skewed society, commuting to school is also sensitive to the social bias. In Kanpur, a larger percentage of schoolchildren travel shorter distances and use the most environmentally friendly modes, such as walking, cycling, and riding a cycle rickshaw, however these modes are also the most susceptible in India.

Sarangi & Manoj (2020) used two multinomial logit model to provide basic insights on the escorting and mode choice decisions of members – faculties, staff, and married students – of an urban university in New Delhi, India. The researchers discovered that when household size grows, the likelihood of dads dropping off/picking up children on personal mode drops for families living outside the campus, but increases for families living on campus. On-campus residents' mothers are more likely to escort their children on active modes, but off-campus residents' mothers are less likely to escort their children on active modes if they work for the government.

Latent variables such as commuter's attitude and perception also play an important role on mode choice decisions apart from the usually studied variables such as the travel time, travel cost and income. And to address this gap Sarkar & Mallikarjuna (2018) developed an Integrated Choice and Latent Variable (ICLV) model based on the analyzed data from Agartala, capital of Tripura state, in the north-eastern part of India to understand the effect of latent variables on mode choice. The variables (relating to flexibility and comfort) of this model were statistically more significant than the usual significant variables (e.g., income, age, gender, vehicle ownership, driving license, family size, education, etc.) from the base MNL model found in some previous studies. The latent variables were significantly explained by education, age, and gender and the comfort desire happened to increase the probability of using personal cars rather than non-motorized options as transport mode.

Perception studies show that improvements in non-motorized transport facilities positively influenced road users’ mode choice decisions regarding NMVs while also significantly increasing the satisfaction among commuters regarding the safety and convenience (Zhou et al., 2020).

2.3 Previous studies on non-motorist safety

Cai et al. (2017) proposed a negative binomial model and a joint model structure of the negative binomial (NB) and logit models to investigate the influence of exogenous factors and the impact of macro-level characteristics on non-motorist crashes. After collecting data from 594 Traffic Analysis Districts (TADs) in Florida, various variables related to crash, traffic and roadway, commuting characteristics along with usual socio-demographic variables were considered. Deviance information criterion (DIC) was computed to compare the 2 models. Result analysis showed that Joint model (DIC= 4206.8) outperformed the NB model (DIC= 4327.32) and the most significant safety factors were- signalized intersection density and proportion of population age 65 or over.

Studies employing univariate models fails to acknowledge common unobserved factors that affect multiple road users. So, Lee et al. (2015) developed a multivariate CAR (Conditional Autoregressive) model for non-motorist crashes at the macroscopic level and compared it with a univariate CAR model. The study concluded that multivariate CAR models outperform the univariate ones and high correlations in errors between crashes by modes justify the adoption of multivariate model.

Huang et al. (2017) performed a similar study also employing spatial correlations among various intersections especially important in urban road network. Using the collected data from 198 intersections of Hillsborough County, Florida, 3 models were developed using Bayesian approach: - a multivariate spatial model (model 1); a univariate spatial model (model 2) and a multivariate model without spatial correlation (model 3). Finally, the models were compared using 2 different goodness-of-fit measures- the posterior mean deviance and Deviance Information Criterion (DIC). The empirical analysis demonstrated the superiority of the multivariate spatial model and the significance of correlation by crash mode and spatial correlation in multimodal crash analysis for urban intersections. Osama & Sayed (2017) found that mode correlation has a higher impact on model performance than spatial correlation in the case of exposure crash models, but have a lower impact in the case of joint crash models.

(Yasmin et al., 2021) developed exposure models using hurdle-negative binomial models, crash count models using negative binomial models, and crash proportions by severity models using ordered probit fractional split models due to a lack of "true" non-motorist exposure data in previous crash prediction models and integrated demand & crash prediction models for active modes. The non-motorist exposure models were developed using data from the NHTS and FDOT databases, while the non-motorist safety analysis used data from the CARS and S4A databases. The anticipated count/proportion events were used to calculate the predictive performance of the estimated exposure and safety models, which were then compared to observed values across different zones. The study concluded that non-motorist friendly infrastructures have a mixed effect on non-motorist safety, that policy implications for improving non-motorist safety should be identified by considering all known exogenous elements in identifying the appropriate tools, that more non-motorized friendly facilities are likely to encourage more people to use non-motorized mode, and that these measures are in targeted zones.

Meena et al. (2014) analyzed the accidents associated with non-motorized mode e.g., cycle rickshaws in city of Lucknow, North India; studied nature of the injuries sustained while finding out the contributing factors to such crashes. Collecting data from King George medical college trauma center, prospective studies were run on patients and analysis were run by SPSS software package with statistical significance set at p=0.05. Variables like age, type of crash, time of crash and injury patterns were considered. Results concluded that overloading of rickshaw is the most common crash factor while the most common cause of injury was collision with a moving vehicle which is followed by falling off the rickshaw.

Apart from crash model development and statistical analysis, some studies like Beitel et al. (2018) also used interactions and automated video conflict analysis to Assessing safety of non-motorized shared spaces. After presenting methods for automated video analysis of non-motorist interactions at intersections in non-motorized shared space, Surrogate safety measures (SSMs) were derived novel for such environments. Five SSMs, one behavioral measure, two traffic flow measures and two event-based measures were calculated and analyzed. Speed and non-motorist density were shown to be negatively correlated, while conflict rate and density were positively correlated suggesting that the derived SSMs demonstrated adequate levels of safety. Statistical differences were also shown between conflict types defined based on intersecting angle and road user configuration. For example: when road users crossed at an angle (Type 3 interaction), it was significantly less likely that they will be involved in a conflict.

The tendency for the number of accidents to increase less than in proportion to traffic volume is known as safety-in-numbers (Elvik & Goel, 2019). Tasic et al. (2017) determined whether the effect of Safety in Numbers exists on a macroscopic level, for non-motorized vehicular users and provided a detailed set of indicators that could represent exposure and relate these indicators to the expected number of crashes for vehicles, pedestrians, and bicyclists. Generalized Additive Model (GAM) was used to develop the areal safety modeling framework for six crash types and crash rates vs exposure was analyzed for all crash types to justify 'safety in numbers' theory. Crash rates vs Exposure analysis showed the increase in crash rate (though total number of crashes are expected to increase as the exposure increases) to be much lower than the rate at which the exposure increases. Thus, the theory of 'safety in numbers' is validated.

Goel et al. (2018) presented a spatial analysis of VRU fatalities (which included non-motorists) in Delhi to assess their geographic variation with respect to built environment, demographic factors, and traffic characteristics. The author employed a Bayesian hierarchical method with a Poisson-lognormal regression model to give a geographical analysis of VRU road fatalities using wards as areal units. Fatality risk was found to have a negative relationship with socioeconomic status (literacy rate), population density, and the number of roundabouts, and a positive relationship with the percentage of the population who worked, the number of bus stops, the number of flyovers (grade separators), and vehicle kilometers traveled. In comparison to no flyover, the presence of a flyover raises the relative risk by 15%.

2.4 Previous studies on NMV safety in context of Bangladesh

Ahsan & Sufian (2014) presented a study on safety issues of NMVs, their involvements in road accidents while finding out the factors affecting such risks. Data was collected from ARI, BUET and field surveys in Mirpur & Bonmra-Hatikamrul Highway, Rajshahi while the author did analysis done using MAAP 5 software. Findings revealed that NMVs were involved in 11% of the total accidents from 1998-2010 where 67% of them were fatal with a 50% casualty rate. Collision with heavy vehicles is one of the main reasons of NMV accidents. And the most influencing factors were - over speeding and careless driving. Hoque et al. (2008) examined the mobility and safety challenges of Vulnerable Road Users (VRUs) in the context of sustainable urban transportation development. Vulnerable Road Users (VRUs), which includes cycle rickshaw occupants, account for the vast majority of urban travel (approximately 80%), and they account for nearly 80% of fatal road traffic accidents.

CHAPTER 3: METHODOLOGY AND DATA

3.1 Introduction (Overall Workflow)

This chapter covers the methodological strategy used in this study in a step-by-step format and a brief overview on the collected data. The goal of this study was to uncover the underlying factors that influence the perception of road users' on NMV safety in the standpoint of developing countries and to establish a causal relationship between the elements. Because such components are frequently interdependent and impacted by prior beliefs, conditional probability can be utilized to demonstrate a causal relationship between them using the Bayesian Belief Network (BBN). This chapter will provide a brief but detailed introduction to Bayesian Belief Network (BBN), as well as a demonstration of its usefulness to our research.

The workflow that was followed in this study is represented diagrammatically in Figure 32.

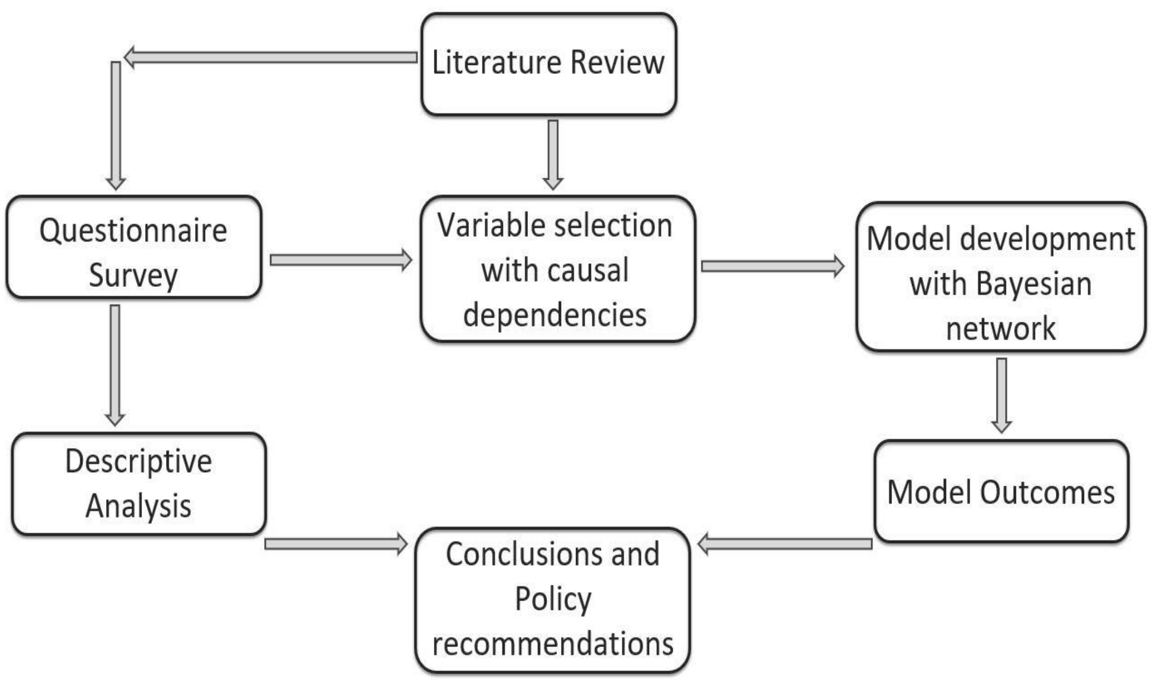


Figure 32: Workflow diagram

Our study started with a comprehensive and thorough literature review. Then using the knowledge gathered from the literature review we prepared a questionnaire survey. Data were collected from a field survey where the relevance and effectiveness of the questionnaire were judged earlier by pilot study and focus group discussions (FGD). The variables for developing the Bayesian network were selected utilizing the information and data from the literature review and the questionnaire survey. The selected variables were then fitted into Bayesian network in the form of DAG (Directed Acyclic Graph). The established model was pruned and optimized based on experts' judgement and knowledge gained from thorough literature review. Finally using the model outcomes and through descriptive analysis of the data from the questionnaire survey, we draw conclusions and suggest some relevant policies for better NMV safety.

3.2 Methods

3.2.1 Bayesian Belief Network (BBN)

In this study, the Bayesian Belief Network (BBN) is implemented to understand the underlying relationship between selected variables. The Bayesian framework is based on the Bayes hypothesis also known as the Bayes rule (Wang & Vassileva, 2005).

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \qquad (1)$$

(A) is the probability of occurrence of A and $P(B)$ is the probability of occurrence of B. $P(A|B)$ indicates the probability of occurrence of A given that B has already occurred and $P(B|A)$ is the probability of B given that A has already occurred. With probability theory and graph theory, the BBN illustrates probabilistic network models. A Bayesian network's graphical and probabilistic structures are the two main components as shown in figure 2. The graph G = (N, E) can be described by a collection of nodes with N = $\{N_1, ..., N_p\}$ and a set of edges with E ⊆ N x N. Nodes N represent variables in any BBN, and E represents the interdependence of the variables using arrows between them. The joint probability density indicating the probabilistic link between nodes in a BBN is given by Equation 2.

$$F(N1, \dots, Nn) = \prod F(Ni \mid parent(Ni)) \quad (2)$$

The conditional probability table (CPT) is used to visualize the joint probability density function and build the BBNs' probabilistic structure. The CPTs help to visualize the joint probability density function and build the BBN's probabilistic structure. The BBN is a directed acyclic graph (DAG), which means that nodes cannot be connected at both ends. There are two sorts of nodes that can be created. The parent node appears before any edge, followed by the child node(Quddus & Hossain, 2021).

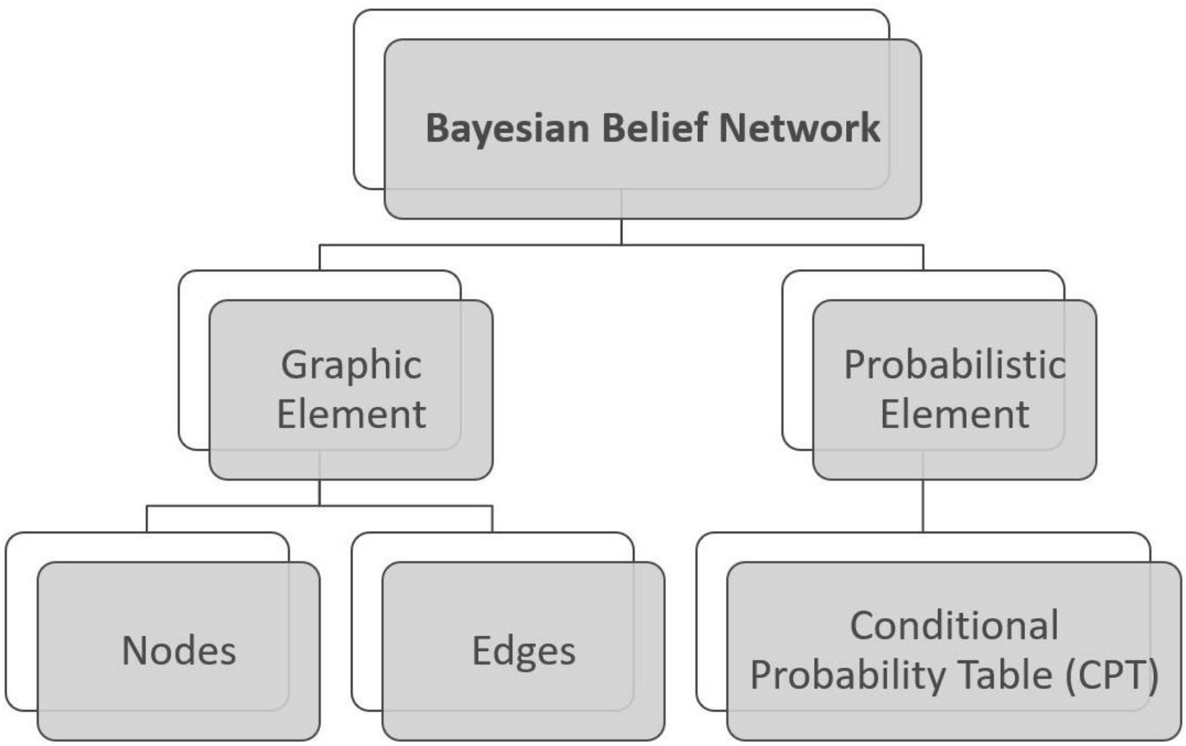


Figure 33: Components of BBN

To learn structure and parameters, the academic edition of GeNIe3.0 is utilized. For structure learning, the Peter-Clark (PC) approach is used. GeNIe learns parameters from both complete and partial samples using the expectation maximization (EM) algorithm.

3.2.2 GeNIe Workspace

GeNIe is a software program that was created at the University of Pittsburgh. This program can be used for decision-making and graphical representation of the union of probability and network occurrences. GeNIe is useful for studying noisy data and uncertainty measures and can be used to analyze Bayesian networks. Calculating a Bayesian network with a high number of interconnected nodes might be difficult at times, but GeNIe is well equipped to handle such challenges. GeNIe 3.0 Academic Version was used for structural learning (network building) and parameter learning in our research (preparation of CPT). GeNIe offers several analysis options after parameter learning is complete, such as observing prior and posterior marginal probability, sensitivity analysis, tornedo diagram, etc.

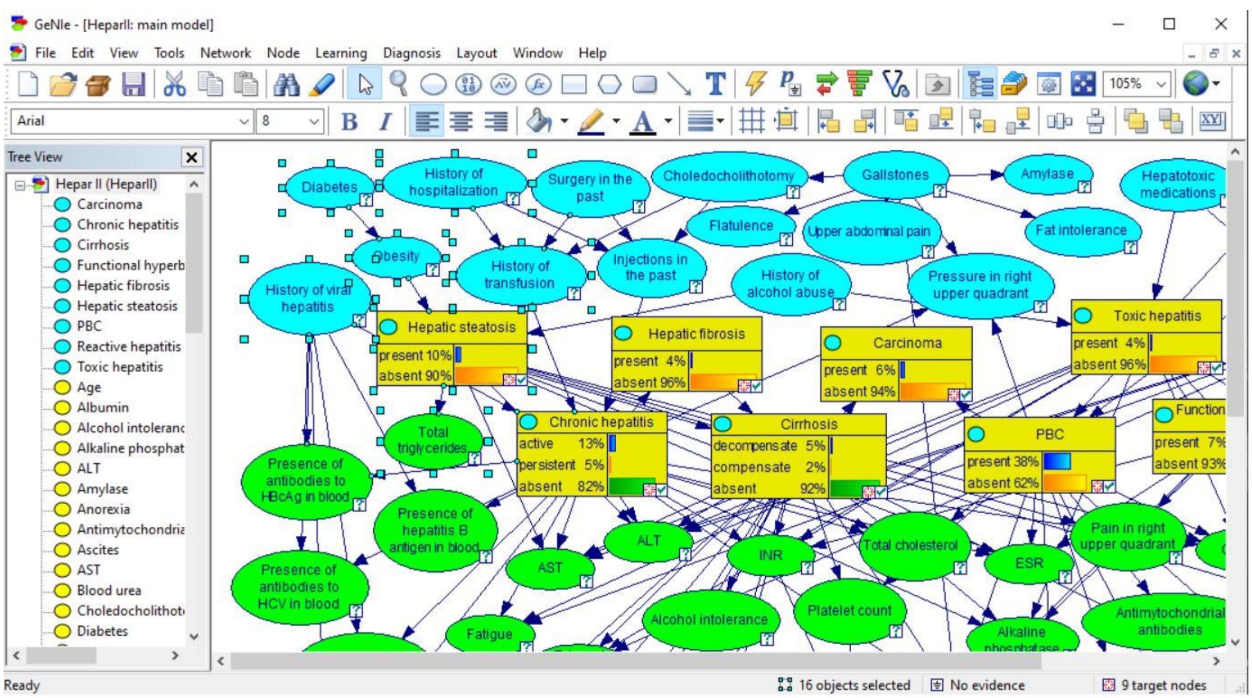


Figure 34: GeNIe workspace example

3.2.3 Model Development

The initial Bayesian network was obtained from GeNIe by structural learning using PC algorithm. The network was then modified based on the sensitivity analysis, strength of influence of the variables, as well as a review of relevant literature. The built-in expectation-maximization (EM) algorithm is utilized to create marginal probabilities of all nodes. The arrow moves from the parent node to the child node, as seen in Figure 4, and it is acyclic. The depicted DAG is built using past research findings and the PC algorithm's structural learning. The final Bayesian network and the associated variables are shown in Figure 35.

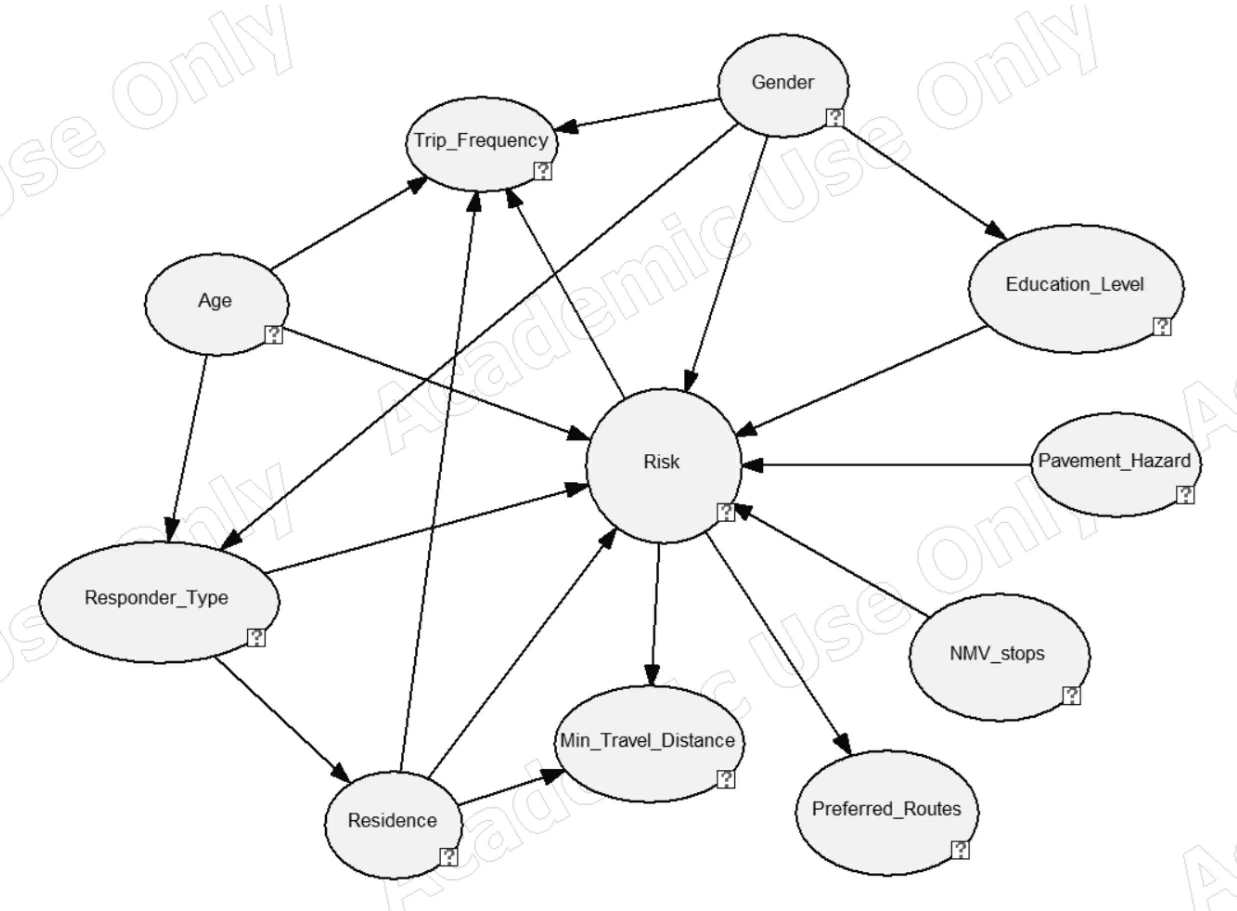


Figure 35: Bayesian network for 'NMV risk perception'

3.2.4 Model Validation

Model validation is a process for assessing whether the model accurately represents the functionality of an application. Leave One Out (LOO) method was used for validation as it is the most efficient method with feasible computation time. LOO is a cross-validation method where the network is trained on all records within the data set except the target variable. The receiver operating characteristic (ROC) curve graphically depicts the number of different cut points and their associated sensitivity vs. 1-specificity (i.e., false positive rate), demonstrating the advantages of a specific predictor/predictive model by allowing multiple cut-points to be identified for different applications based on the 'cost' of misclassification. The area under the curve (AUC) assesses a predictor's efficiency by comparing (testing) two or more predictive models. Generally, an AUC value above 0.7 is considered an acceptable value for model validation. In our study, the NMV risk perception model achieved 0.92 which is an indicator of a good functioning model.

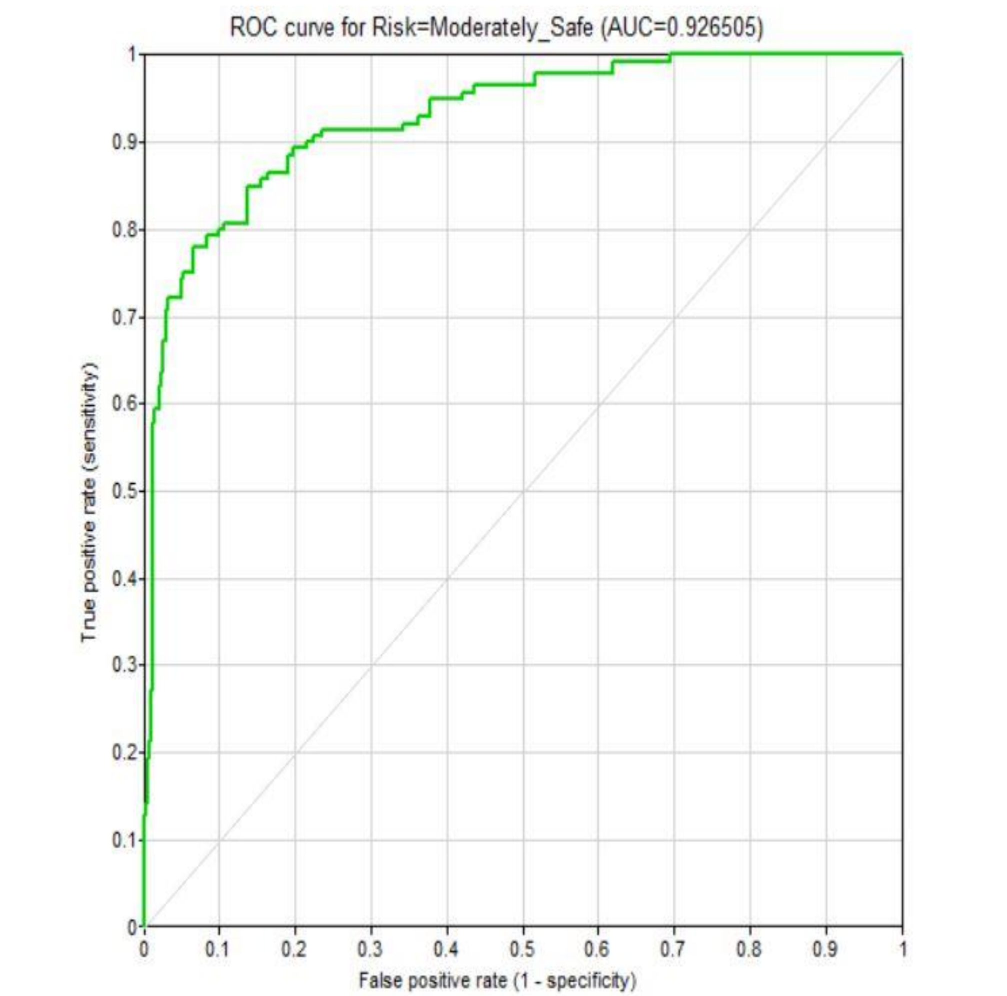


Figure 36: ROC curve for 'NMV risk perception' model

A confusion matrix, also known as an error matrix, is a table pattern that aids in visualizing a model's performance. Each column in a confusion matrix reflects the actual class, whereas each row represents the anticipated class. Here is the confusion matrix for the NMV risk perception model-

		Predicted		
		Highly_Risky	Moderately_...	Moderately_...
Actual	Highly_Risky	**36**	54	7
	Moderately_Risky	72	**153**	72
	Moderately_Safe	1	18	**121**

Figure 37: Confusion matrix of NMV risk perception model

3.3 Study area and data collection

The survey data was gathered from several locations throughout Dhaka. The survey data was carefully chosen to reflect the demographic and psychographic characteristics of the majority of Bangladesh's population.

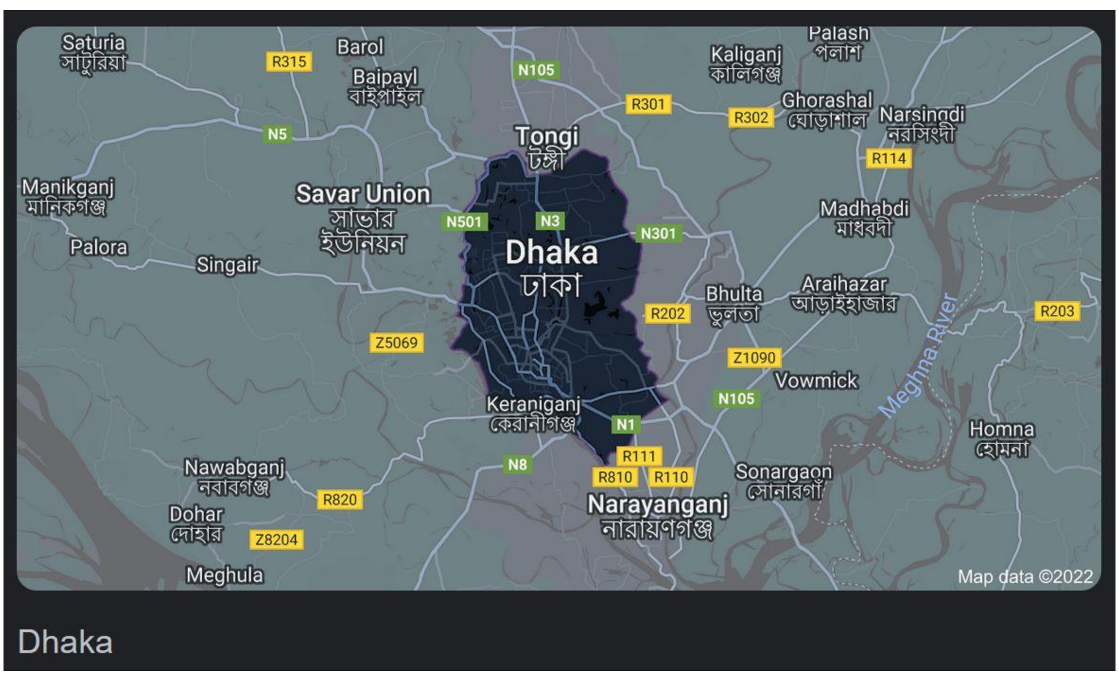


Figure 38: Study area of the survey

The questionnaire survey was distributed to a number of surveyors who then implemented the survey on a number of Dhaka residents belonging to different road user groups and it yielded 534 valid samples. Based on a literature search and the opinions of transportation experts, the questionnaire for NMV safety perception was created. A focus group discussion (FGD) was also held to determine the survey form's relevance to local residents. Responders were informed about the purpose of the survey before they were presented with the questionnaire. Besides the demographic section, the questionnaire survey consists of two major portions from the safety perception and the operational perception. The safety perception section of the survey contains 16 items, marking on 5-point Likert-type scale. Table 7 shows relevant descriptive statistics for necessary variables. According to the total score (out of 80), the samples are divided into three groups: moderately safe (lower quartile: ≤ 47), moderately risky (between upper and lower quartile: 47-69), and highly risky (upper quartile: > 69).

Table 6: Statistics of questionnaire survey 'NMV safety perception

Variable	Item	Frequency	Percentage (%)
Gender	Female	108	20.22
	Male	426	79.78
Education Level	Graduate_or_Diploma	80	14.98
	Higher_Secondary	99	18.54
	Illiterate	49	9.18
	Primary	122	22.85
	Secondary	184	34.46
Pavement Hazard	Asphalt_cracks	93	17.42
	Excessive_Speed_Bumps	127	23.78
	Manholes	70	13.11
	Potholes	244	45.69
NMV Stops	Beside_bus_stops	363	67.98
	Intersection	27	5.06
	Local_Arterial_road_junction	107	20.04
	Mid_blocks	37	6.93
Preferred Routes	Fastest_Route	6	1.12
	Route_with_NMV_exclusive_lane	59	11.05
	Safer_Route	449	84.08
	Shortest_Route	20	3.75

Min Travel Distance	Between_1_to_2_km	339	63.57
	Between_3_to_4_km	94	17.58
	Less_than_1_km	101	18.84
Residence	Azimpur	47	8.80
	Dhanmondi_Newmarket	186	34.83
	Gulshan	99	18.54
	Mirpur	134	25.09
	Mohakhali	58	10.86
	Mohammadpur	10	1.87
Responder Type	Bus_Driver	51	9.55
	Car_Driver	63	11.80
	Motorcycle_Rider	72	13.48
	NMV_Driver	164	30.71
	Pedestrian	184	34.46
Age	Between_18_to_25	73	13.67
	Between_25_to_35	267	50.00
	Between_35_to_50	156	29.21
	Between_50_to_60	19	3.56
	Less_than_18	19	3.56
Trip Frequency	Daily	108	20.17
	Several_times_a_month	110	20.69
	Several_times_a_week	316	59.14
Risk	Highly_Risky	167	31.33
	Moderately_Risky	189	35.38
	Moderately_Safe	178	33.29

Table 7 shows that majority of the respondents were male holding about 80% of the total responder number. It is a representation of the male dominant society of a developing country like that of Bangladesh. The percentage of illiteracy among the road users were the lowest (9.18%) when we divided them based on their education level. Most of the respondents completed their secondary level of education which was a representation of 34.46% of the total responder number. 34.83% of the responders were from Dhanmondi and New-market area. Most of the respondents who participated in the survey were general pedestrians, and 50% of the respondents aged between 25 to 35. A total of 167 responders judged NMV movements to be highly risky though almost 60% of responders took an NMV trip several times a week.

CHAPTER 4: ANALYSIS AND RESULT

4.1 Introduction

After finishing data analysis using BBN model, this chapter provides the study's main findings. The data from the survey was initially re-categorized and re-distributed using descriptive statistics. The data was then fine-tuned and fitted into a Bayesian network structure. The network's nodes were adjusted and tested to see how each variable affected the target variable. The model was subjected to several analyses, including sensitivity analysis and tornedo diagrams. The model's accuracy was additionally checked using the GeNIe software's built-in model validation tool. After the analysis process was completed, all of the research findings were compiled and presented in this chapter concisely.

4.2 Model Analysis

The initial phase in the GeNIe software analysis process is parameter learning. For parameter learning, GeNIe employs the default EM (Expectation-Maximization) algorithm. After parameter learning, the marginal probabilities of all nodes in the network were calculated. For a particular occurrence of the target variable, the marginal probability is the sum or union of all the probabilities of happenings of other variables. The target variable in this study was the 'Risk' level.

As long as the dependent variable is unchanged, the prior marginal probabilities of variables in a Bayesian network structure are identical to the observed data. The posterior marginal probability can be observed using GeNIe for any change in the dependent variable's events. The study looked for changes in safety perception and socio-demographic parameters as a result of the forced changes in target variables. As illustrated in Figure 35, the arrow moves from the parent node to the child node, and it is acyclic.

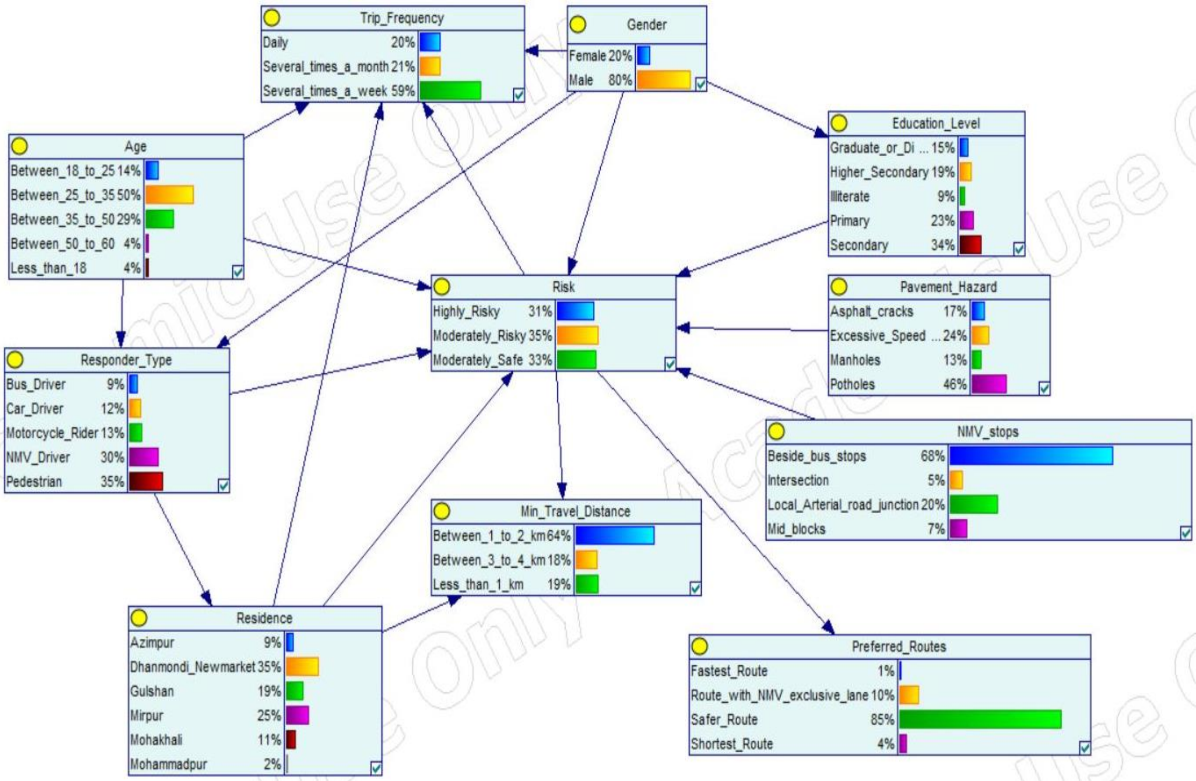


Figure 39: Prior marginal probability distribution diagram

Figure 39 shows the prior marginal probabilities of each node, whereas Figure 40 shows the posterior marginal probabilities when the target variable's state 'Highly risky' is set as evidence. Similarly, Figure 41 and 42 shows the posterior marginal probabilities when 'Moderately risky' and 'Moderately safe' is set as evidence in the target variable respectively.

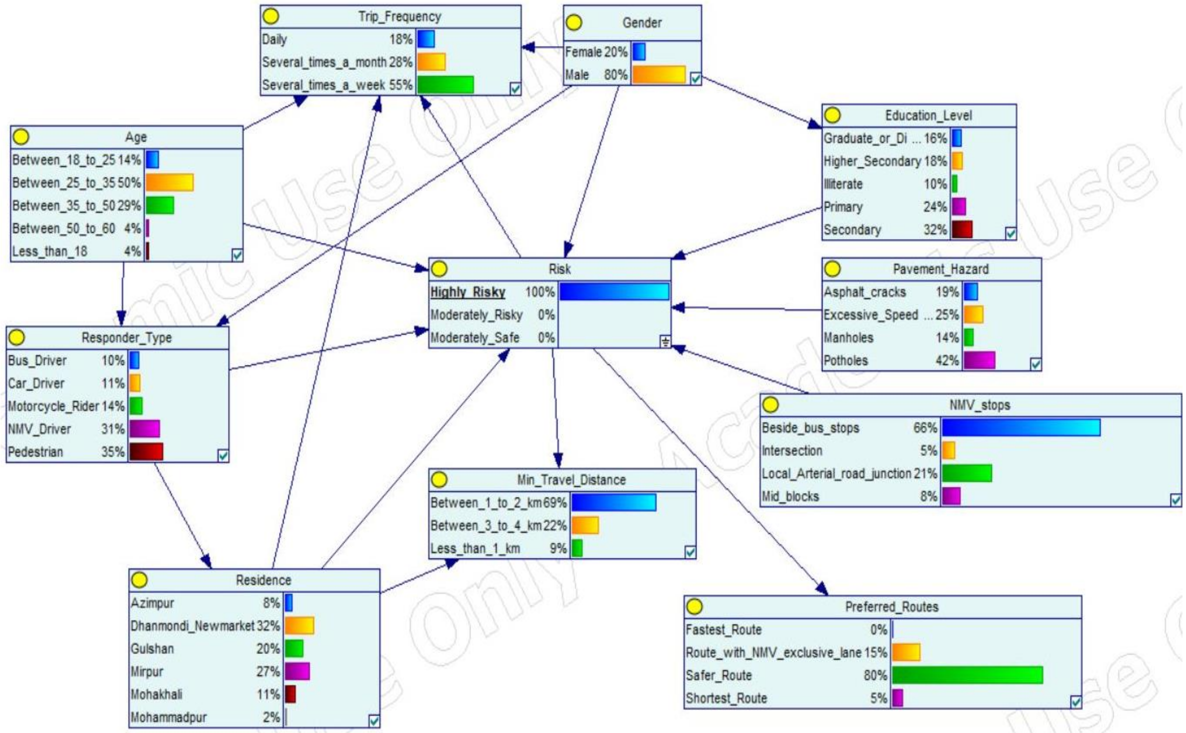


Figure 40: Posterior marginal probability distribution- highly risky set as evidence

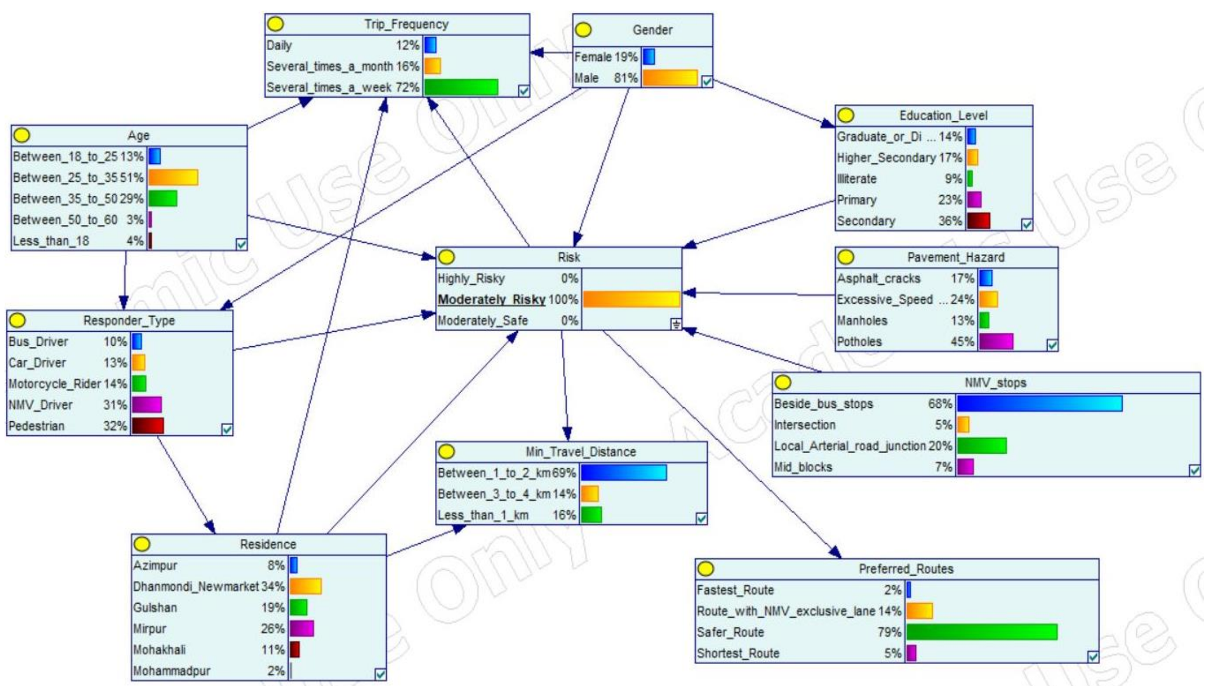


Figure 41: Posterior marginal probability distribution- moderately risky set as evidence

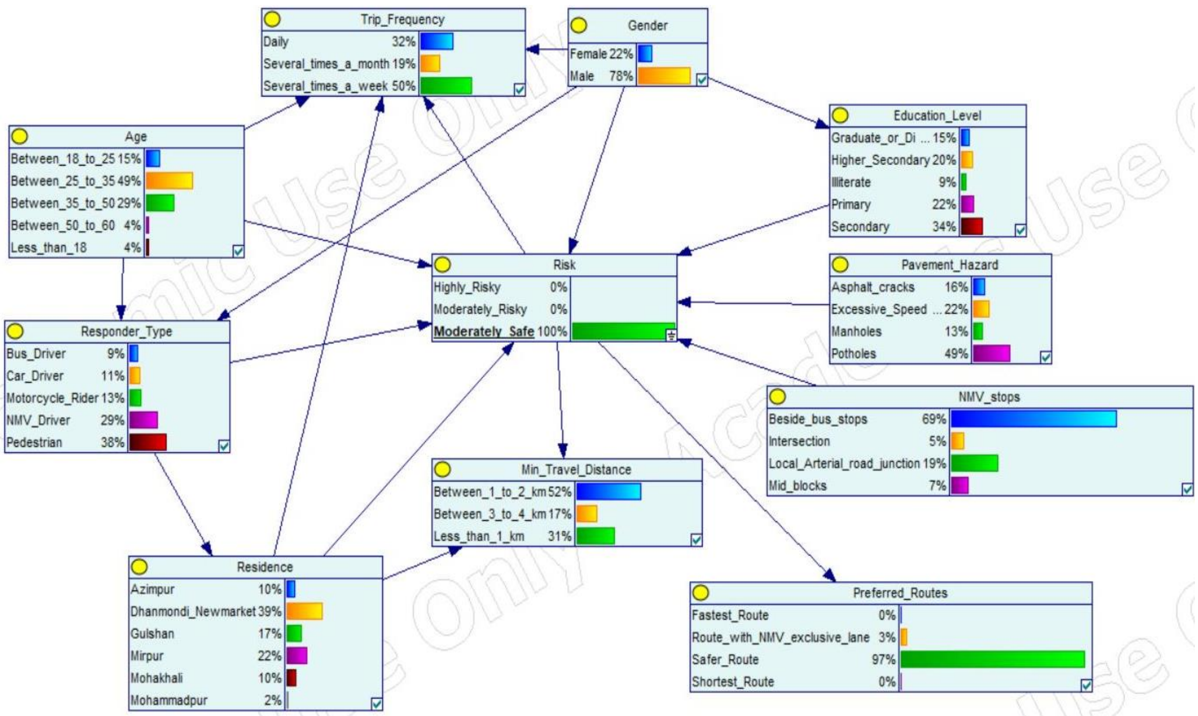


Figure 42: Posterior marginal probability distribution- moderately safe set as evidence

The posterior marginal probabilities of each node were observed for all three of the evidence of target variable 'Risk'. Table 8 illustrates the outcomes of the observation.

Table 7: Marginal probabilities of all nodes (in percentage) while evidence is set for 'Risk

Variable	Item	Evidence (%)		
		Risk		
		Highly Risky	Moderately Risky	Moderately Safe
Gender	Female	20	19	22
	Male	80	81	78
Education Level	Graduate_or_Diploma	16	14	15
	Higher_Secondary	18	17	20
	Illiterate	10	9	9
	Primary	24	23	22
	Secondary	32	36	34
Pavement Hazard	Asphalt_cracks	19	17	16
	Excessive_Speed_Bumps	25	24	22
	Manholes	14	13	13

	Potholes	42	45	49
NMV Stops	Beside_bus_stops	66	68	69
	Intersection	5	5	5
	Local_Arterial_road_junction	21	20	19
	Mid_blocks	8	7	7
Preferred Routes	Fastest_Route	0	2	0
	Route_with_NMV_exclusive_lane	15	14	3
	Safer_Route	80	79	97
	Shortest_Route	5	5	0
Min Travel Distance	Between_1_to_2_km	69	69	52
	Between_3_to_4_km	22	14	17
	Less_than_1_km	9	16	31
Residence	Azimpur	8	8	10
	Dhanmondi_Newmarket	32	34	39
	Gulshan	20	19	17
	Mirpur	27	26	22
	Mohakhali	11	11	10
	Mohammadpur	2	2	2
Responder Type	Bus_Driver	10	10	9
	Car_Driver	11	13	11
	Motorcycle_Rider	14	14	13
	NMV_Driver	31	31	29
	Pedestrian	35	32	38
Age	Between_18_to_25	14	13	15
	Between_25_to_35	50	51	49
	Between_35_to_50	29	29	29
	Between_50_to_60	4	3	4
	Less_than_18	4	4	4
Trip Frequency	Daily	18	12	32
	Several_times_a_month	28	16	19
	Several_times_a_week	55	72	50

From the analysis we see that when the evidence for the risk perception is set from safe to highly risky users exhibit 12% higher tendency to use routes with NMV exclusive lanes. For the same scenario, usage of NMVs for daily trips is lowered by 14%. A 22% decrease is also seen in making short distanced trips by NMVs. Presence of various pavement hazards also increases a user's high risk perception towards NMVs by 2 to 3%. The marginal probability of a user who perceives NMVs as 'moderately safe' to be aged between 18 to 25 is 15% but it decreases to 14% if the evidence is set up as 'highly risky'. Similarly, the marginal probability of the road user being a pedestrian increases from 35% to 38% and that of residing in

Dhanmondi and Newmarket area increases from 32% to 39% if the evidence is set from 'high risk perception' to 'moderately safer perception'. Moreover, the marginal probability of NMV stop to be at local and arterial road junctions decreases from 21% to 19% for a similar change in evidence. Female road users were seen to perceive NMVs to be safer on our roads compared to their male counterpart.

4.2.1 Sensitivity Analysis of 'NMV risk perception model'

To gain a better understanding of the most significant factors, a sensitivity analysis was performed on the existing network. GeNIe displays the effect of variation in the target variable in a sensitivity analysis. The dark red variables have the most influence on the target variable. The impact gradually reduces as the red color intensity lowers. White variables have a very minimal impact on the target variable, while grey variables have no impact at all.

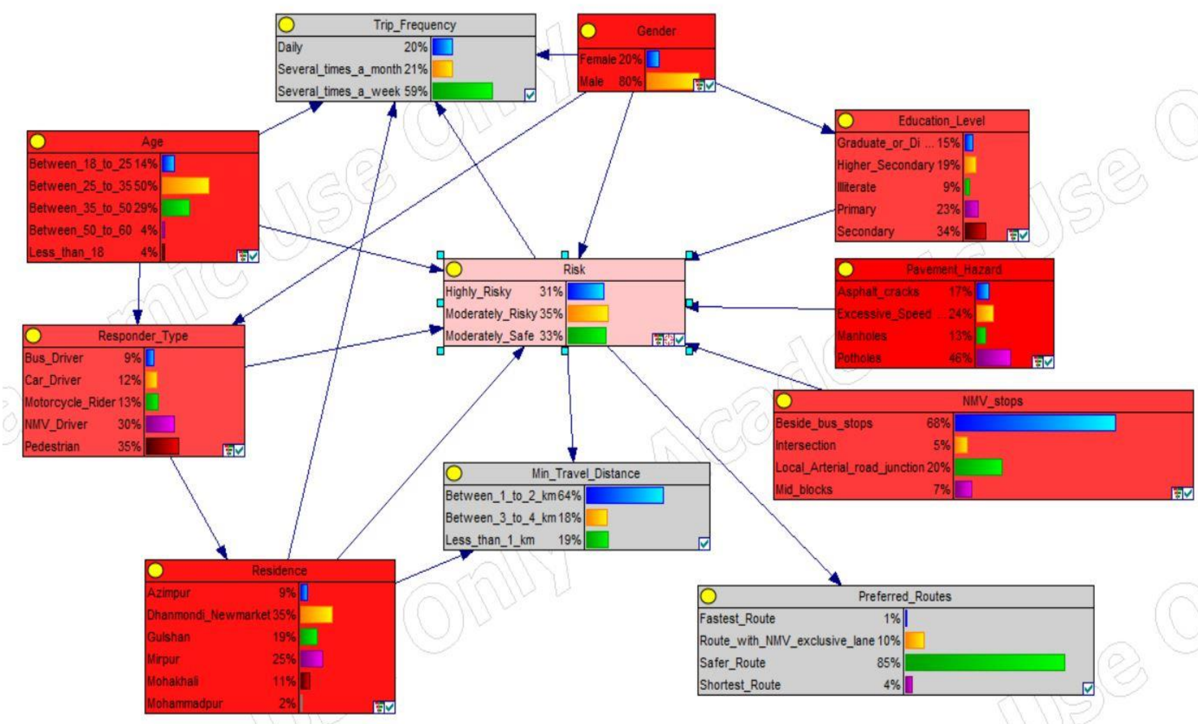


Figure 43: The BBN and key variables for 'Risk'

The sensitivity analysis shows that 'Gender', 'Education level', 'Pavement hazard', 'Age' and 'Residence' are the most significant variables. And 'Responder type' and 'NMV stops' are found to be the second most important. A tornado diagram in sensitivity analysis identifies the most significant state of a variable for a selected state of the target variable. The tornado diagram for our model is shown in Figure 44.

Figure 44: Tornado diagram in sensitivity analysis when the risk perception is 'Highly Risky'

CHAPTER 5: CONCLUSION & RECOMMENDATION

5.1 Introduction

This chapter summarizes the major findings of the study and makes realistic recommendations based on the findings. Policymakers, transportation planners, vehicle users, and other relevant people may find the recommendations and consequences useful. The limitations and future scopes of our investigation were highlighted in the final remark.

5.2 Major findings

Identifying key factors influencing a road users' perspective on safety regarding non-motorized vehicle movement was a primary objective of this study. The sensitivity analysis showed that Age, Gender, Residence and Pavement Hazard type are the most significant variables while type of the responder and location of NMV stops came second. As shown from the analysis, presence of various pavement hazards increases the possibility of high risk perception towards NMVs e.g., cycle rickshaws. Since presence of hazards like speed bumps and cracks on the road will be a certain threat to NMV movements due to their poor roll-over stability. The probability of high risk perception towards NMV is the most when stops are at mid-block locations.

The probability of having high risk perception towards NMV is more in older aged groups than in the middle aged. And female road users tend to have safer perception towards NMV than their male counterpart. Safer perception towards NMV also tends to increase with the increase in the education level of a road user. The probability of perceiving NMVs on the roads as 'high risk' is more among bus drivers than among the car drivers. Road users from Mirpur had the highest probability of high risk perception while users from Dhanmondi area had the lowest which is a representation of poor road conditions for NMV movement in Mirpur area.

Furthermore, users had a 12 percent increased tendency to choose routes with NMV exclusive lanes when the evidence for risk perception is set from safe to highly risky, according to the analysis. The use of NMVs for daily journeys is reduced by 14% in the same situation. NMVs are also used for traveling shorter distances at a 22 percent lower rate.

5.3 Policy Implications

From the perspective of a developing country, the goal of this study was to uncover the underlying factors that affect safety perceptions towards NMV movement. A thorough survey was done for this aim, and various road users were asked about sociodemographic and safety perception-related information. Key factors were identified by fitting the obtained data into a Bayesian network and rigorous analysis. The research findings were able to shed light on factors that should be brought under government policy in order to improve non-motorized vehicular safety on the roads. Because the research was able to uncover the key factors of safety perception, such findings argue for substantial policy implications. Residence, existence of pavement hazards, location of NMV stops along with socio-economic variables influences a road user's perspective on NMV safety, which supports previous studies (Goel et al., 2018; Khan et al., 2014). Various pavement hazards are riskier for non-motorized vehicles than they are to motorized vehicles due to the unsafe structure and dynamics of NMV like cycle rickshaws. NMVs are also more accident prone in various areas due to this reason (Ahsan & Sufian, 2014). As a result, it's critical to improve NMV, particularly cycle rickshaw design. Some potential improvements include (i) decreasing the overall weight of NMVs (ii) providing gears to NMVs (modern world pedicabs is a successful example of this) (iii) Adding nighttime reflectors. Since road users show increased tendency to choose routes with NMV exclusive lanes when they feel susceptible during NMV trips, provisions of parallel service roads or NMV-exclusive lanes can be kept on both sides of highway and busy streets. In our country, the majority of NMV pullers are uneducated. They have little or no understanding of how roads work. As a result, they frequently cause traffic congestion and accidents on the road which in return encourage negative perception of road users towards NMV use. Thus authorities should take steps to educate and train the rickshaw pullers and also modernize the licensing process. There must also be strict enforcement of laws, fines, and sanctions to make NMV pullers and also other road users more aware of the traffic rules and laws.

5.4 Limitations and future scope

From a variety of perspectives, this study is significant. This study found factors that influence people's perceptions of safety concerning NMVs, which have not been addressed by local researchers. Furthermore, a causal relationship between the identified factors was created, allowing the effect of one variable on another to be easily detected. This study is one of the first of its kind to look into such aspects in this way. However, there are certain flaws in this research that must be addressed.

One of the limitations is the data as it is extracted from a self-assessed questionnaire. There is a possibility of self-reporting bias. In the future, alongside the self-reported questionnaire survey, a naturalistic non-motorized driving study can be conducted to deduct scenario-based driving safety scores which will be an indicator of the level of risk. The use of video surveillance and vehicle-recording tools in the survey can also greatly improve the data quality. Stakeholders, policymakers, and relevant authorities must actively participate in the policy implications and recommendations presented in this study, which can be difficult. Finally, in order to reach the implementation phase, the proposals made through this analysis must be economically and financially sustainable.

SECTION 4: MOTORCYCLE RIDE SERVICE PROVIDERS' DRIVING BEHAVIOR REGARDING APP-BASED AND CONTRACT-BASED RIDERS

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

A motorcycle is a two-wheeled motor vehicle whose design varies widely to serve various functions, including long-distance transport, urban traffic navigation, cruising, sport, racing, and off-road riding.(Gumel et al., 2017). Affordability and accessibility make motorcycles one of the most popular modes of transportation in cities across the globe, as they are easy to navigate across tiny and poorly planned roadways (SA & MM, 2018).

It is estimated that some 200 million motorbikes, such as mopeds and motorcycle-powered bicycles, are used worldwide. (Shuhei, 2014). In 2010, powered two- and three-wheelers (PTW) accounted for 50 percent of registered vehicles in low- and middle-income nations (49.6 and 45.8 percent, respectively) and 6.8 percent in high-income countries (Ivers et al., 2016 cited in SA and MM, 2018)). The number of motorbikes worldwide increased by 27 percent from 2010 to 2013, according to the World Health Organization (WHO, 2015).

Despite the large number, motorcyclists are more likely to be involved in a collision than automobile drivers. Motorcycle accidents are 6–13 times more likely than those involving other vehicles. More than a quarter of all road deaths worldwide are caused by motorcycles, increasing in numbers every year (Yousif et al., 2020).

Bangladesh is a South Asian country with a middle income and a very high road fatality rate. There is a large disparity between the Dhaka city's transportation needs and the city's supply, as well as bad traffic management and poor public transportation services. One of the primary causes of the shortage is a good transportation environment is the absence of a sufficient transportation system(Rahman & Ali, 2019). People are increasingly interested in private transportation services, and motorcycles in particular. The Bangladesh Road Transport Authority (BRTA) has registered 25,87,651 motorcycles in the country as of April 2019, of which 6,49,003 are registered in Dhaka(Rahman & Ali, 2019). However, it is not possible for everyone to have their own motorcycle. And therefore, ride-sharing services are extremely popular in Bangladesh now.

The rapid growth of internet technology has made it possible to create online platforms where customers can directly deal with businesses. This medium enables taxi (both car and motorbike) customers to compare and select the service that best meets their demands in the transportation business (Suhartanto et al., 2020). App-based ride-sharing has been available in Bangladesh beginning in 2014. There are currently eight ride-sharing services operating, primarily in metropolitan areas (Financial Express, 2018).

Despite its widespread use, users of motorcycle ride-sharing have expressed concern about several issues and complaints, including the unprofessional attitude of drivers, inadequate safety equipment, a lack of training for drivers, and the employment of untrained bikers by service providers, which frequently results in accidents, and an excessive fare rate, among others (New Age, 2018).

In addition to those issues, there is a new one that is being debated right now: "Contract-Based Riding Service." The term "Where are you going?" is frequently heard among the bikers. Before responding, they stated, "Will not go through App. Will you go to the agreement?" before responding. It was requested that the app be turned off and that the contract be implemented. Consequently, no portion of the rental is required to be paid by the driver of the Ridesharing Application. Many people believe that this poses a threat to public safety. If the app is closing, it means that the driver is defrauding his employer and that the company will not be able to track him. Neither party will accept responsibility for the incident. (Daily Bangladesh, 2019) .

Numerous studies have been conducted to investigate motorcycle rider behavior, but none have been conducted to investigate the driving behavior of motorcycle ride service providers when providing rides to riders who use apps or who contract with them. A probabilistic network can analyze the driving behavior based on the driver's license condition, age, bike quality, trip duration, and so many variables. However, these factors are not always mutually independent; more often than not, the combined effect of multiple factors affects an individual's perception of the effectiveness of driving behavior. Conditional probability can be used in conjunction with Bayesian theory to establish a relationship between the variables.

1.2 Purpose and Objectives

It is important to identify the factors that have a greater impact on the driving behavior of app-based or contract-based riders because this information can be used by policymakers and transportation corporations to implement and execute measures that promote the use of safety restraints and the use of these restraints. Our research aims to identify the most important factors influencing driving behavior in Bangladesh, regardless of whether the service is provided through an app or a contract.

Regarding our objective, "Assessing contract based or app-based motorcycle service providers' safety and riding behavior," the factors that are taken into account are:

- Based on demographics.
- Based on Trip details.
- Based on other safety measures.

1.3 Scope of the Study

Specifically, the study is interested in determining the most important factors that influence riders' behavior when it comes to trips that are booked through an app or through a contract. During the survey phase of this study, the majority of the respondents and participants in the focus groups belonged to the Dhaka region. Riders from a variety of locations participated in the survey, ensuring that the results were as representative as possible.

1.4 Thesis Outline

The thesis is divided into six chapters, each of which is discussed in detail. The chapters are briefly introduced in the sections below:

Chapter 1: **Introduction-** This chapter provides an overview of the research, including the background, problem statement, purpose, and objective.

Chapter 2: **Literature Review**- This chapter talks about the relevant pieces of literature that helped come up with the best research plan.

Chapter 3: **Methodology and Data**- Scope, limits, and data gathering processes are covered in this chapter, along with the gradual working process of the research and the method utilized to analyze the data.

Chapter 4: **Analysis and Results-** This chapter examines the analysis of gathered data and interprets the conclusions acquired.

Chapter 5: **Conclusion and Recommendations**- This chapter summarizes the research's key findings and discusses policy implications.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The study of driver behavior in relation to safety restraints is a topic that is frequently discussed among transportation researchers. The lack of studies on motorbike service providers riding behavior through an app or contract based in Dhaka city prompted researchers to consider conducting studies to determine the most important factors affecting their safety and behavioral perspective on the road. This chapter begins with a discussion of the various behavioral impacts on safety restraints that have been observed. It is then discussed in depth in detail the summary of relevant literature that has already been conducted regionally and internationally, along with their methodology and final findings.

2.2 Motorbike Service Providing System

Since the invention of the motorcycle, it has always been regarded as a mode of private transportation. Afterwards, it was transformed into a ride-sharing service for use in rural areas where the transportation sector is underdeveloped or nonexistent. In recent years, the tremendous growth of the internet has made this ride-sharing service more accessible to everyone through the use of apps. Those app-based service providers work for commercial companies, and they are connected to those companies through the company's app. Concerns about the safety of riders and users are the responsibility of the companies. They keep an eye on the system and help to formulate policy. Riders are required to pay a certain percentage of their fare to the company for each ride they take.

However, there have been some annoyances with this ride-sharing system in recent years. App-based riders reach out to customers through apps and then propose to them that they enter into a contract without using the apps, thereby avoiding the need to pay a commission to the app-provider company. And in this scenario, there are concerns about security and safety.

2.3 Previous Studies on Ride-Sharing Service

Through self-reporting, the Motorcycle Rider Behavior Questionnaire (MRBQ) was developed to assess the behavioral factors that influence motorcyclists' crash risk, such as errors and violations, as well as the use of motorcycle safety equipment.(Sakashita et al., 2014). In the survey, participants were asked about their demographics, riding activities, riding-related attitudes and behaviors, the motorcycles they ride, their driving experiences, rider training experiences, and motorcycle crashes. The human aspect has the greatest impact on passenger pleasure and perceived value(Suhartanto et al., 2020).

(Rahman & Ali, 2019) Stated that many people who work in the transportation industry think that ride-sharing services on motorcycles in Bangladesh should be welcomed, but they should be used with care. The "Ridesharing Service Guideline 2017" in Bangladesh lets people use their own vehicles for business purposes through apps. People who use apps to get around are becoming more interested in ride-sharing services that use motorcycles because they can save time by cutting travel time in cities with bad traffic. From 2014, Bangladesh has been able to share rides through apps. There are now eight ride-sharing services in the country, most of which are based in big cities.

When it comes to developed countries, the OMT (Online Motorcycle Taxis) service is a niche market; however, due to traffic congestion and the relatively low cost of this transportation mode, it is important in many developing countries.(Suhartanto et al., 2020). The dimensions of OMT service quality were evaluated using exploratory factor analysis, which was used in this study. This study evaluated the measurement model's validity and reliability using variance-based structural equation modelling (SEM) and partial least squares (PLS).

GrabBike started in Thailand on August 5, 2015. The Singapore-based ride-hailing app, GrabTaxi, had been in the Thai market for two years, upsetting local transportation businesses that relied heavily on expensive taxi licenses. This is what it had done all over Southeast Asia. The new service became popular quickly, mostly because it fixed one of the biggest problems with taxis in Bangkok.(Sopranzetti, 2021)

Gumel et al., (2017) Explored, Many Nigerians, especially the uneducated, rely on the commercial motorcycle transport known as okada for their livelihood (largely concentrated in

Northern Nigeria). He used a modified Mincer equation to look at the data, and the results show that the age of okada riders, where they live, and whether or not they have a license all have a positive effect on earnings, while age and the average fare charged per trip have a negative effect on earnings. The results of his study also show that okada riders can make anywhere from N500 to N2,800 per day. In this case, education has nothing to do with how much money a commercial motorcyclist makes.

The study (Mendoza et al., 2020) focuses on a specific type of public transportation: motorcycle taxis that use an online booking app. The discussion of how this research is done is based on qualitative research. Qualitative research is meant to look at the human aspects of a given topic, and certain qualitative methods look at how customers see and experience the service quality of this Motorcycle Taxis via online booking application.

In terms of transport dynamics, there are notable disparities between the southern and northern regions of Ghana. Throughout contrast to southern Ghana, where commercial vehicles generally known as "trotro" are the predominant method of transportation, motorbikes/tricycles are prevalent in northern Ghana, particularly the UWR. Due to the absence of a reliable public transportation system, the poor condition of the roads, and the high expense of purchasing and maintaining private vehicles, many residents of northern Ghana rely on motorcycles/tricycles (Konkor et al., 2019).

In the past, researchers have looked into topics such as motorcycle driving behavior, the effects of app-based riding services, the state of ride sharing services in developing countries, and a variety of other topics. Although there have been some studies on contract-based ride sharing systems, none have been conducted to determine whether there is a difference in riders' driving behavior between app-based and contract-based systems in terms of safety perception between the two types of systems.

CHAPTER 3: METHODOLOGY AND DATA

3.1 Introduction

This chapter presents the methodological approach used in this study in a step-by-step format and data collection strategy. The goal of this research was to uncover the underlying factors influencing driver behavior from the perspective of an app-based or contract-based ride-sharing service, as well as to establish a causal relationship between the factors. Because such factors are frequently interdependent and influenced by prior beliefs, conditional probability can be used to establish a causal relationship between them using the Bayesian Belief Network (BBN). This chapter will provide a brief but thorough introduction to Bayesian Belief Network (BBN), as well as a demonstration of its applicability to our research.

3.2 Methods

The work flow of the research is outlined in the Figure 45:

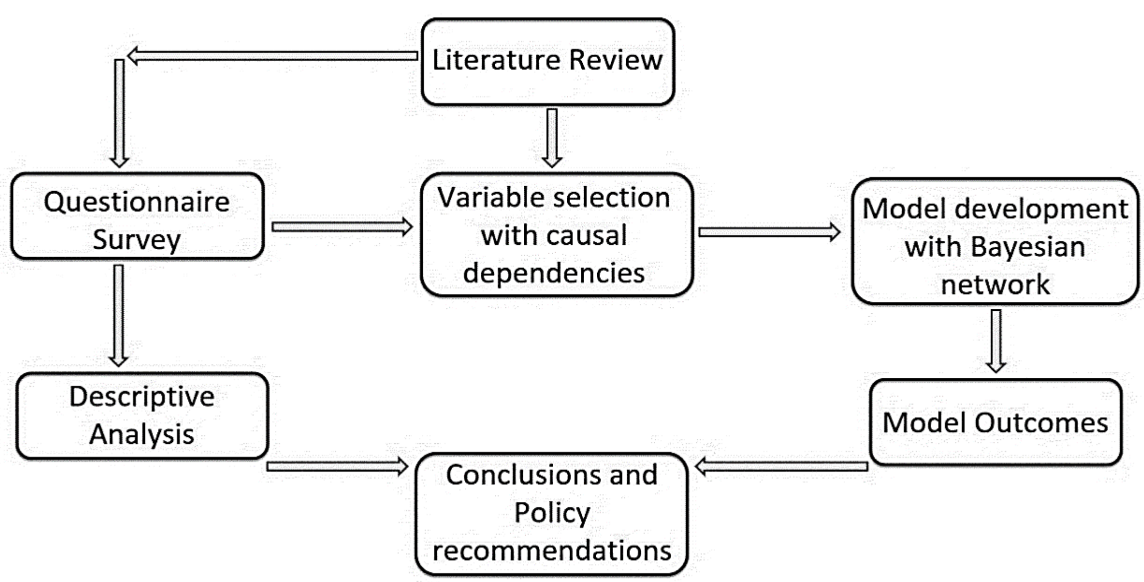


Figure 45: Workflow of research

The research work started with a thorough review of the literature, which was used to make the questionnaire survey. Data were gathered from a field survey. Earlier, a pilot study and FGD were used to figure out whether or not the questionnaire was useful and how well it worked. The collected data was then put into a DAG-shaped Bayesian network (Directed Acyclic Graph). The model that was already in place was cut down and improved based on what experts thought and what they learned from a thorough review of the literature. After all of the steps listed above were done, the model was ready to be asked questions and get answers.

3.3 Bayesian Belief Network (BBN)

In this study, the Bayesian Belief Network (BBN) is used to find out what the real relationship is between things like how drivers feel about their rides, their demographics, and how these things affect how they drive. Bayesian network is a graphical model that shows how a set of variables depend on each other based on certain conditions. The conditional dependencies are shown as a Directed Acyclic Graph (DAG), which is a useful tool for seeing the probabilistic model, figuring out how random variables relate to each other, and seeing what their posterior probability is based on the evidence we have. In DAG, each random variable is called a "node," and arcs keep them linked. The nodes on the side of an arc where it starts are called "mother nodes," and the rest are called "child nodes." A Conditional Probability Table (CPT) is also part of the Bayesian network. It shows how likely it is that one variable will lead to another. The Bayes hypothesis, also called the Bayes rule, is the foundation of the Bayesian framework (Yang, 2019) –

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$$

P(A) is the probability that A will happen, and P(B) is the probability that B will happen. P(A|B) is the probability that A will happen if B has already happened. P(B|A) is the probability that B will happen if A has already happened. A Bayesian network is a graph that shows the joint probability distribution and can be written as the product rule. –

$$(X_1,\ X_2, \ldots\ldots X_n) = \prod_{i=1}^{n} P(X_i | pa(X_i))$$

The structure of a Bayesian network can be learned from data or can be a mix of expert knowledge and structural learning. The mixture method was used to build the network for this study. The data from the questionnaire was put into GeNIe 3.0 Academic Version, and the PC algorithm was used to do the structural learning. The PC algorithm is a popular method for finding causes that is based on constraints. This algorithm uses the Conditional Independence (CI) test to figure out how the structure of the network is put together .The Expectation Maximization (EM) algorithm is used by GeNIe to get the joint probability distribution by learning the parameters. The EM algorithm is a way to find the most likely estimate when there are hidden variables. EM starts by estimating the values of latent variables. Then, to improve the estimation, the process is repeated. The iteration process has two steps called the "Expectation Step" (E-Step) and the "M-Step" (Maximization Step). Iteration keeps going until the two steps meet.

3.4 GeNIe Workspace

GeNIe is a piece of software that was made at the University of Pittsburgh. This software can be used to help make decisions and show how probability and network events fit together on a graph. GeNIe can be used to look at Bayesian networks and is a very useful tool for looking at noisy data and measures of uncertainty. When a Bayesian network has a lot of nodes that are all connected to each other, it can be hard to figure out how to calculate it. GeNIe can easily analyze these kinds of problems.

GeNIe 3.0 Academic Version was used in our research for both network formation (structural learning) and parameter learning (parameter learning) (preparation of CPT). After parameter learning is done, GeNIe gives you different ways to look at the data. For example, you can look at the prior and posterior marginal probability, do a sensitivity analysis, make a tornedo diagram, find the strength of an influence, etc.

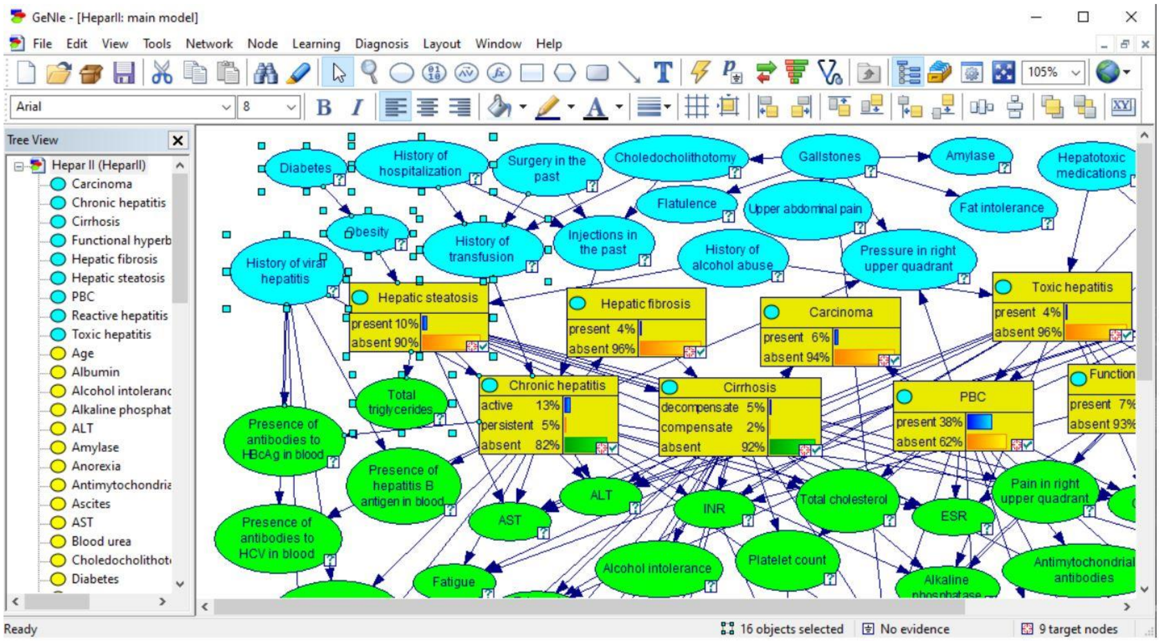


Figure 46: GeNIe workspace Example

3.5 Model Development

GeNIe 3.0 uses the variables from the survey data that have been put in order. In the GeNIe 3.0 Academia version, the variables were used to make the first network using the PC algorithm. Under the questionnaire, the variables are made. The "driving behavior" variable is made up of a few questions from the analysis of relevant literature. The final network was built with numerous trial and error, engineering judgment, literature review. Then this is the result, which meets the likely condition about driving behavior.

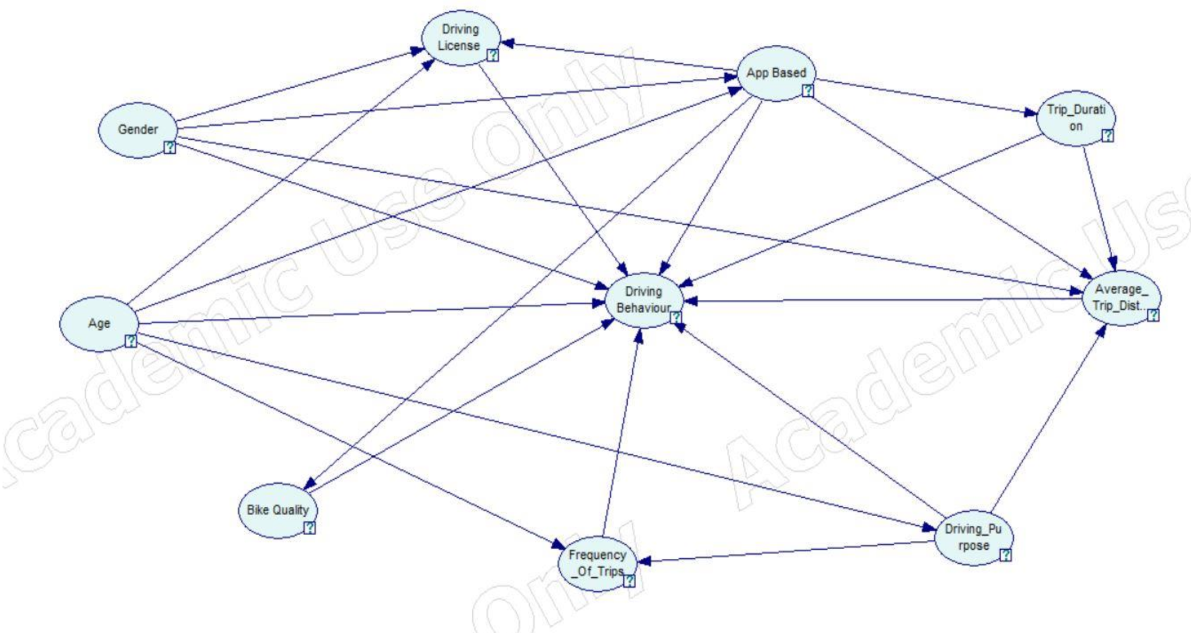


Figure 47: Bayesian Network of Driving Behavior

3.6 Model Validation

GeNIe's built-in validation tool was used to check how accurate the models were. For validation, the Leave One Out (LOO) method was used because it is the most effective method that can be done in a reasonable amount of time. LOO is a cross-validation method in which the network is trained on all of the records in the data set except for the target variable. Receiver Operating Characteristic (ROC) curve is a way to show the results of the evaluation. The ROC curve is a plot of sensitivity versus false positive rate. The line along the diagonal shows that a model has a 50 percent chance of making an accurate prediction. The Area under the ROC Curve (AUC) is a value between 0 and 1, and the closer it is to 1 the better the model is doing (Park, Goo, & Jo, 2004). In general, for model validation, an AUC value above 0.7 is considered to be a good value. In our study the (AUC) value is 0.93 which represents that the model is a well validated model.

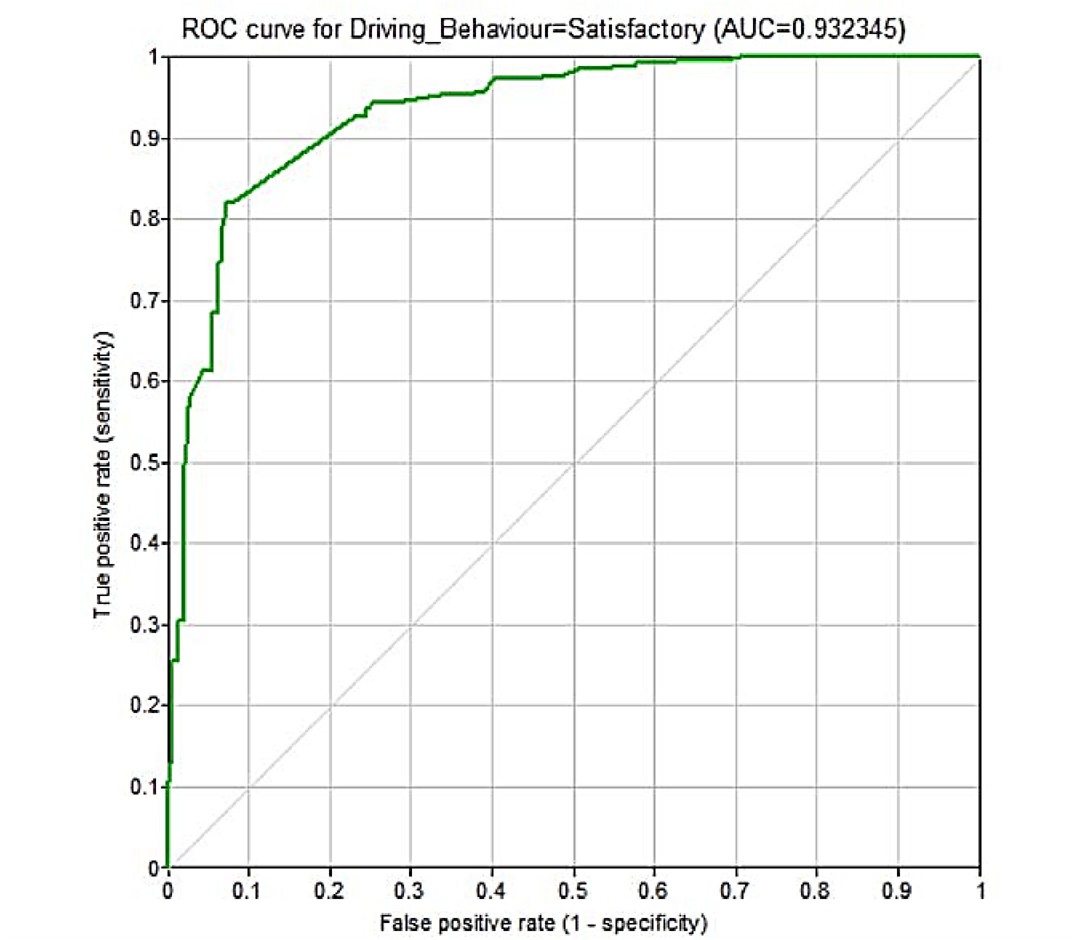


Figure 48: ROC curve for Driving Behavior Model

A confusion matrix, also called an error matrix, is a table that shows how well a model works. Each column in a confusion matrix shows the actual class, and each row shows the class that was predicted. Here is a view to the confusion matrix for the driving behavior model.

		Predicted		
		Highly_Risky	Risky	Satisfactory
Actual	Highly_Risky	**92**	166	10
	Risky	163	**402**	50
	Satisfactory	39	24	**238**

Figure 49: Confusion Matrix of Driving Behavior Model

3.7 Study area And Data

The survey data was gathered from various locations throughout Dhaka. The locations were carefully chosen to ensure that both contract and app-based riders could be found.

Figure 50: Study Area of the survey

The data was gathered through the use of a questionnaire based on a review of the DBQ (driving behavior questionnaire) literature. Riders were asked some demographic questions as well as their license status, trip details, and whether they wanted to use an app-based or contract-based ride-sharing service, among other things. The survey was conducted among 1200 riders, with a total of 1184 responses being filtered out. Using the sorted data, a total of ten variables were selected for analysis to determine their influence on driving behavior.

The driving behavior perception section of the survey marking on 5-point Likert-type scale. According to the total score (out of 120), the samples are divided into three groups: Satisfactory (lower quartile: ≤ 49), risky (between upper and lower quartile: 49-72), and highly risky (upper quartile: > 72). The selected variables are:

Table 8: Statistics of questionnaire survey 'Ride Service Provider Driving Behavior''

Variables	Item	Frequency	Percentage
Age	Above 35	445	37.58
	Between 18 to 35	737	62.25
	Below 18	2	0.17
Gender	Male	947	79.98
	Female	237	20.02
Driving License	Yes	648	54.73
	No	536	45.27
Ride Sharing Method App Based	Yes	591	49.92
	No	593	50.08
Bike Quality	Bad	8	0.68
	Neutral	1047	88.43
	Perfect	129	10.90
Frequency of Trips	Daily	871	73.56
	Several times a week	115	9.71
	Several times a month	129	10.90
	Several times a year	69	5.83
Trip Duration	Between 60 to 90mins	122	10.30
	Between 30 to 60mins	992	83.78
	More than 90mins	9	0.76
	Less Than 30mins	61	5.15

Average Trip Distance	Between 10 to 20km	671	56.67
	Between 5 to 10km	107	9.04
	Greater 20km	405	34.21
	Less than 5 km	1	0.08
Driving Purpose	Part time job	182	15.37
	Employment	643	54.31
	Recreation	188	15.88
	Others	171	14.44
Driving Behavior	Highly risky	268	22.64
	Satisfactory	301	25.42
	Risky	615	51.94

CHAPTER 4: ANALYSIS AND RESULTS

4.1 Introduction

This chapter shows the main results of the study after the BBN model has been used to analyze the data. At first, descriptive statistics were used to reclassify and redistribute the data from the survey. Then, the data that had been tweaked were put into a Bayesian network structure. The network's nodes were changed and put to the test to find out how each variable affected the chosen target variable. Several types of analysis, such as sensitivity analysis and the Tornedo diagram, were done on the model. Using the GeNIe software's built-in model validation feature, the model's accuracy was also checked. After the analysis step was done, all of the research's results were put together and presented in this chapter.

4.2 Model Analysis

The learning of parameters is the first step in the analysis process when using GeNIe software. When it comes to parameter learning, GeNIe employs the standard EM (Expectation-Maximization) algorithm. After learning about the parameters, we were able to calculate the marginal probabilities of all nodes in the network. The marginal probability is defined as the total or union of all the probabilities of events in other variables for a given event in the target variable. Driving behavior was chosen as the targeted variable in this study so that the effects of other variables could be determined by observing it.

In a Bayesian network structure, the prior marginal probabilities of variables match the observed data as long as the dependent variable stays the same. But with GeNIe, you can see the posterior marginal probability for any change in the dependent variable. The analysis was to observe the changes in other parameters due to force alteration in target variable.

4.3 Analysis of Driving Behavior Model

The driving behavior is categorized as "Highly Risky," "Risky," and "Satisfactory" according to the survey results (out of 120 points) based on a 5-point Likert-type scale. Figure 51 depicts the prior marginal probability distribution for "Driving Behavior," while Figure 52, Figure 53 and Figure 54, depict the posterior marginal probabilities when the target evidence is set to "Highly Risky," "Risky," and "Satisfactory," respectively.

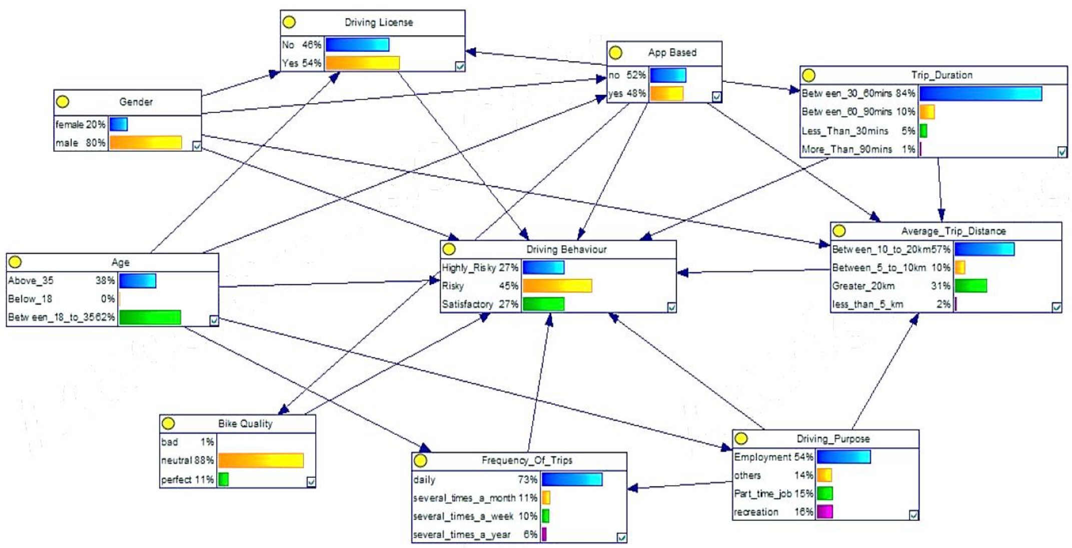


Figure 51: Prior marginal probability distribution diagram of 'Driving Behavior'

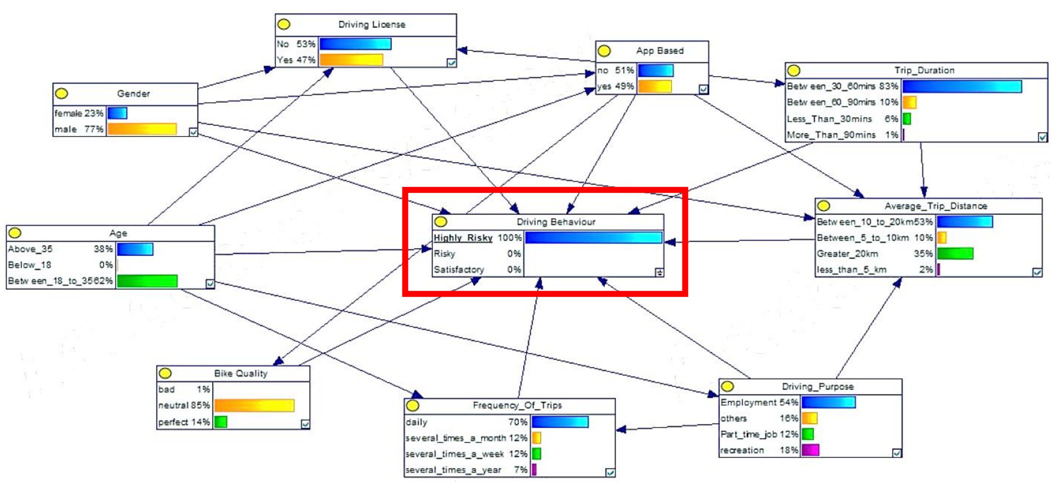


Figure 52: Posterior Marginal Probability Distribution Diagram when then Driving Behavior is 100% "Highly Risky"

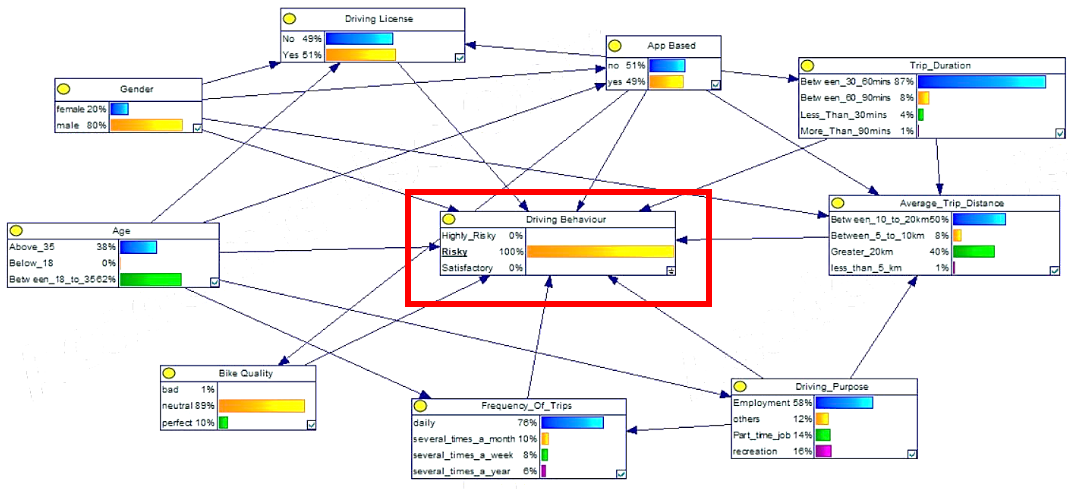


Figure 53: Posterior Marginal Probability Distribution Diagram when then Driving Behavior is 100% " Risky"

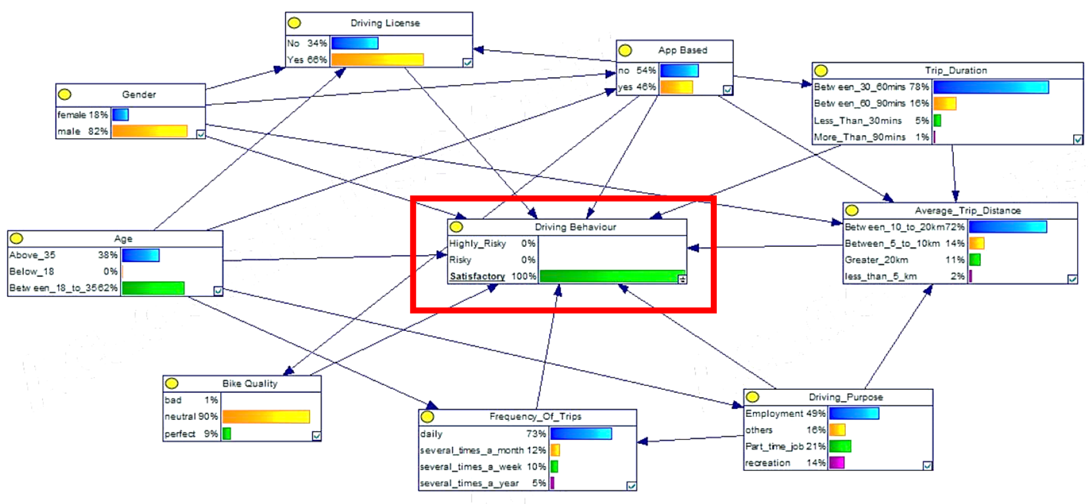


Figure 54: Posterior Marginal Probability Distribution Diagram when then Driving Behavior is 100% "Satisfactory"

The posterior marginal probabilities for three pieces of evidence of node 'Driving Behavior' are shown side by side in Table 10.

Table 9:All nodes marginal probabilities for 'Highly Risky', 'Risky' and 'Satisfactory' state of target variable 'Driving Behavior'

Variables	Item	Driving Behavior (Evidence %)		
		Highly Risky	Risky	Satisfactory
Age	Above 35	38%	38%	38%
	Between 18 to 35	62%	62%	62%
	Below 18	0	0	0
Gender	Male	23%	80%	82%
	Female	77%	20%	18%
Driving License	Yes	47%	51%	66%
	No	53%	49%	34%
Ride Sharing Method App Based	Yes	49%	49%	46%
	No	51%	51%	54%
Bike Quality	Bad	1%	1%	1%
	Neutral	85%	89%	90%
	Perfect	14%	10%	9%
Frequency of Trips	Daily	70%	76%	73%
	Several times a week	12%	8%	10%
	Several times a month	12%	10%	12%
	Several times a year	7%	6%	5%
Trip Duration	Between 60 to 90mins	10%	8%	16%
	Between 30 to 60mins	83%	87%	78%
	More than 90mins	1%	1%	1%
	Less Than 30mins	6%	4%	5%
Average Trip Distance	Between 10 to 20km	53%	50%	72%
	Between 5 to 10km	10%	8%	14%
	Greater 20km	35%	40%	11%
	Less than 5 km	2%	1%	2%
Driving Purpose	Part time job	12%	14%	21%
	Employment	54%	58%	49%
	Recreation	18%	16%	14%
	Others	16%	12%	16%

Based on this study, we can observe that the modification of the age requirements did not result in any major changes. On the other hand, we can observe that having a valid driver's license has a significant impact on how risky or satisfactory the journey is. When rider behavior is deemed to be satisfactory, 66 percent of riders are granted permission to drive, however when rider behavior is deemed to be highly dangerous, 53 percent of riders do not hold valid driver's licenses. Because the value of female riders is significantly lower than that of male riders, the effect of a person's gender on their driving behavior should not be taken into account in this analysis. There is a tangential relationship between driving style and bike quality. When the quality of the bike is exceptionally high, riders have a tendency to drive more roughly.

It is preferable to have a trip that is between 30 and 60 minutes long and 10 to 20 kilometers in distance rather than one that is either shorter or longer. The drivers that commute on a regular basis have a greater degree of expertise, which results in a higher level of customer satisfaction. On the other hand, some of these drivers believe that they have a greater level of expertise than they actually do and so drive riskier rides.

And finally, it can be said that though the driving behavior is not much influenced by the riders riding through app or contract but they feel more satisfactory during contract-based ride.

4.4 Sensitivity Analysis of Driving Behavior Model

A sensitivity analysis was performed on the current network in order to acquire a greater grasp of the most critical components. In a sensitivity study, GeNIe highlights the influence of target variable variation. The variables in dark red have the greatest impact on the target variable. As the red color's intensity diminishes, so does its influence. White variables have a negligible impact on the target variable, while grey variables have no impact.

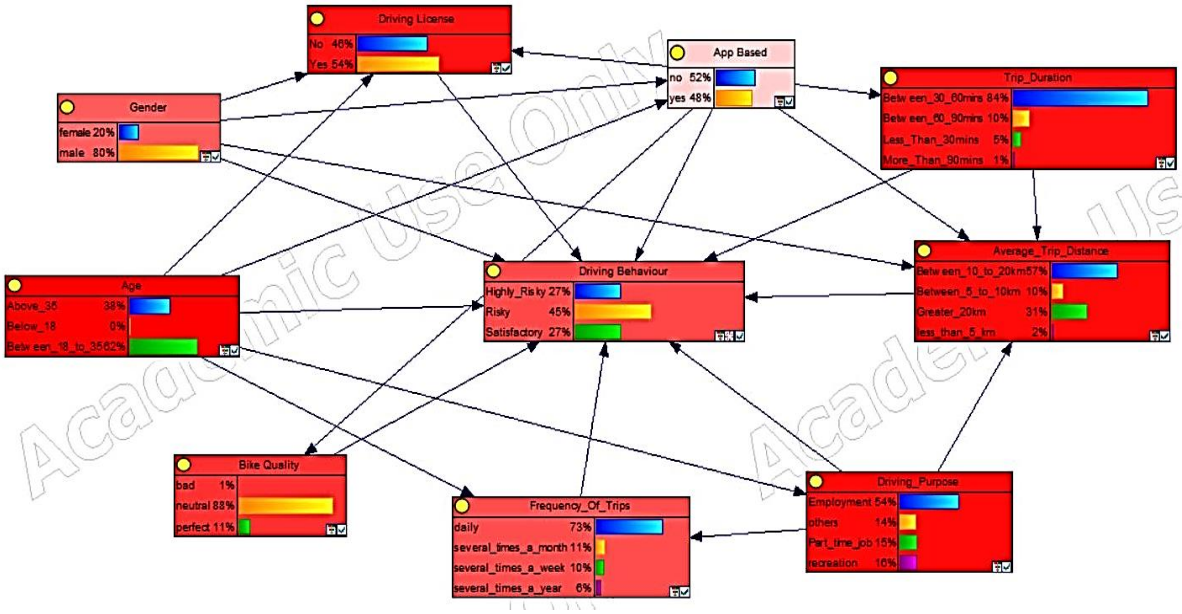


Figure 55: The BBN and key variables for 'Driving Behavior'

The sensitivity analysis reveals that the variables 'Gender' and 'Frequency of travels' are less significant. And 'Ride sharing method' is shown to be the least significant factor. In sensitivity analysis, a tornado diagram identifies the most significant state of a variable for a given state of the target variable. The tornado diagram for our model is shown in Figure 56.

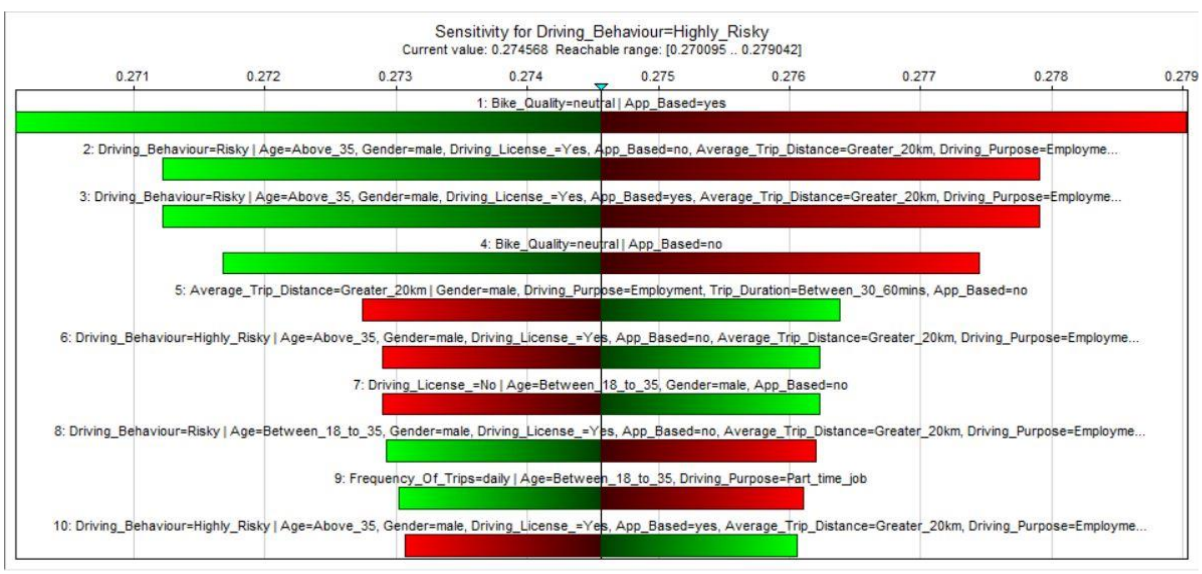


Figure 56: Tornado diagram in sensitivity analysis when the driving behavior is 'Highly Risky'

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter summarizes the study's findings and provides plausible recommendations based on the results. Policymakers, transportation planners, vehicle users, and all other relevant personnel may benefit from the detailed recommendations and implications. To conclude, we have discussed the limitations and future scopes of our investigation.

5.2 Major Findings

This study was conducted out of a concern for public safety in order to discover the factors that influence driving behavior from the riders' point of view. Their perspectives on appropriate driving conduct when operating as a motorbike ride service. In this constantly changing environment, the quickest possible trip are more taken into count. As a result, more and more people are using the motorbike service rather than taxis, CNG, or any of the other available modes of transportation. Therefore, the companies that provide ride sharing services are also experiencing growth. But in recent years, as a result of the commission system, riders have been opting more frequently to go through contract-based services because, in this manner, they are exempt from paying any commission to the corporation. However, because this system is based on contracts, there is no monitoring in place for the riders. As a result, there is a significant threat to the users' safety. And the most important question we want to answer with this research is whether or not their driving behavior alters in any way whether they take a ride based on an app or a contract.

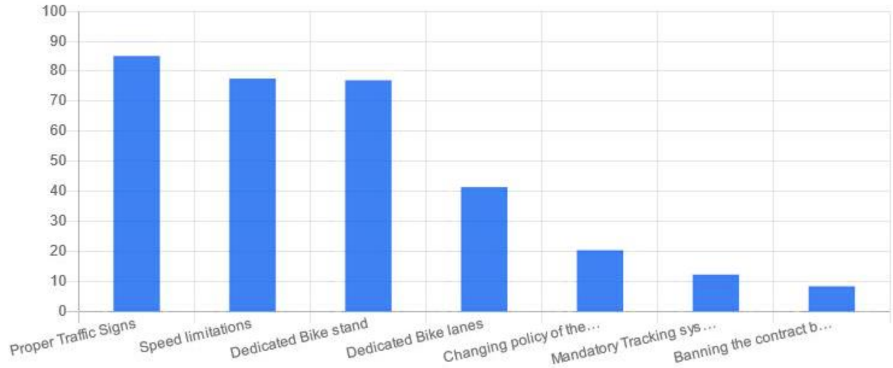
According to the findings of the investigation, it is possible to conclude that their behavior does not alter when they are riding because the rider is using an app or a contract. On the other hand, they favor going through contract-based riding more than app-based riding.

Driving license play the significant role on their riding behavior. When rider behavior is considered satisfactory, 66% of riders are granted permission to drive; conversely, when rider behavior is deemed highly risky, 53% of riders do not possess valid driver's licenses. Trip distance & Trip duration have also influence on their driving behavior.

5.3 Policy Implications

During the survey the questionnaire was set to find out the needs of the riders to have safer roads for motorcycle riders and users along with their riding behavior questionnaire.

So, from the questionnaire survey Figure 57 shows their demand to Government regarding a safer traffic environment for the motorcycle riders. We can see that proper traffic signs is the most wanted thing. Then speed limitation of all vehicles, dedicated bike stand for the ride service providers and dedicated bike lanes for all motor bike riders are some of their other concerns.



Value	Frequency	Percentage
Proper Traffic Signs	1039	85.09
Speed limitations	947	77.56
Dedicated Bike stand	940	76.99
Dedicated Bike lanes	505	41.36
Changing policy of the apps	248	20.31
Mandatory Tracking systems	149	12.2
Banning the contract based riders	101	8.27

Figure 57: Riders demand on Policy Implication for motorcycle riders.

Disparities in knowledge of speed limit and timing to first collision signals the need for strategic ways of improving existing road safety education especially in rural areas where road safety infrastructure such as road signs are unavailable. Speed has been identified as a major deliberate risk-taking behavior contributing to the rise in motorbike collision and the increasing severity of injuries and fatality associated with them. As indicated by the WHO, excess speed is associated with most accidents in urban settings, while inappropriate speeding on poor roads account for a greater part of the collisions in rural and poorly developed roads (WHO, 2015)

For Ghana to achieve the Sustainable Development Goals, particularly Goal 3, target 3.6, it is essential to improve road quality, vigorously implement road safety education to alter risky behaviors, and strictly enforce driving/riding regulations regarding alcohol consumption, helmet use, and speed limits.(Konkor et al., 2019)

Employing drivers who are competent of driving safely, are punctual, understand passenger needs, are courteous to passengers, and are familiar with city traffic in order to avoid traffic jams will allow enterprises to provide a high level of service. The development of such skills and capacities of OMT workers can be accomplished through the recruitment process, the provision of appropriate training for drivers, and the provision of incentives.(Suhartanto et al., 2020)

5.4 Limitations and Future Scopes

The significance of this study can be seen from a variety of angles. This study refers to the unsafe driving variables from the perspective of the riders, despite the fact that the primary objective was to find variety in driving behavior relating app or contract based riding because many studies have been completed except this crucial topic. Therefore, this study is the first one that has been conducted on this issue. Having said that, this study does have a few restrictions, as well as some potential future applications.

This study has a number of flaws, one of which is that the survey was only done from the riders' point of view. However, the viewpoint of the user will be quite important in this regard because a self-assessed questionnaire carries with it a significant risk of self-reporting bias. During app-based or contract-based rides, the inclusion of a harassment-related questionnaire is a suitable alternative for the purpose of determining the riders' behavior with regard to the users. A comparative analysis based on the users' perspective and the riders' perspective can be carried out to determine the real risk factors that are associated with riding a motorcycle. Regarding this matter, a policy making study ought to be carried out in the presence of many stakeholders, policy makers, and relevant authorities in order to put the policies and recommendations into action. The primary desire of everyone is to have access to a reliable and secure transportation system.

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Appendix

Pedestrian Questionnaire

Sample of the questionnaire survey form (Only includes questions used in the study):

Vehicle-to-Vehicle Vendors & Pedestrian Questionnaire

Demographic Information:

Gender: ☐ Male ☐ Female ☐ Transgender ☐ Prefer not to say

Age: ☐ <18 ☐ 18 – 25 ☐ 25 – 35 ☐ 35 – 50 ☐ 50 – 60 ☐ 60 – 65 ☐ 65+

Education:
☐ Illiterate ☐Drop out
☐ No formal Education ☐Formal Education

Monthly Income (BDT):
☐ < 10k ☐ 35-45k
☐ 10-15k ☐ 45-55k
☐ 15-20k ☐ 55-65k
☐ 20-25k ☐ 65-100k
☐ 25-35k ☐ 100k+

Dwelling Condition:
☐ Personal ☐ Others: ________________
☐ Rental
☐ Slum
☐ Office Quarters

Risk perception:

Boarding & Alighting

Question	Vehicle to Vehicle Vendor	Pedestrian
Do you run to get into a vehicle (Bus) that is in motion (running)?	□ Never □ Rarely □ Sometimes □ Often □ Always	□ Never □ Rarely □ Sometimes □ Often □ Always
Will you get out of a running	□ Never	□ Never

bus?	□ Rarely □ Sometimes □ Often □ Always	□ Rarely □ Sometimes □ Often □ Always
Will you get out of the bus in the midblock of the road?	□ Never □ Rarely □ Sometimes □ Often □ Always	□ Never □ Rarely □ Sometimes □ Often □ Always
While getting out of the bus, do you look behind to check for any incoming vehicle? (Motorcycle, rickshaw, CNG, etc.)	□ Never □ Rarely □ Sometimes □ Often □ Always	□ Never □ Rarely □ Sometimes □ Often □ Always

Crossing

Question	Vehicle to Vehicle Vendor	Pedestrian
In a road, when there is free flow of vehicles, do you prefer grouped or ungrouped jaywalking?	□ Grouped □ Ungrouped	□ Grouped □ Ungrouped
If there is barrier in the road, will you cross the road?	□ Never □ Rarely □ Sometimes □ Often □ Always	□ Never □ Rarely □ Sometimes □ Often □ Always
In case of partially broken or faulty barriers, will you cross the road?	□ Never □ Rarely □ Sometimes □ Often □ Always	□ Never □ Rarely □ Sometimes □ Often □ Always
Do you look at both directions before crossing?	□ Never □ Rarely □ Sometimes □ Often □ Always	□ Never □ Rarely □ Sometimes □ Often □ Always
When you are in a hurry and need to join/meet someone on the other side of the road, do you forget to look at both directions before crossing?	□ Never □ Rarely □ Sometimes □ Often □ Always	□ Never □ Rarely □ Sometimes □ Often □ Always
Suppose, there is a bus in the middle of the lane, and you are in a hurry so you need to get into the	□ Never □ Rarely □ Sometimes	□ Never □ Rarely □ Sometimes

bus, If there is a heavy flow of traffic, will you attempt to get into that bus?	□ Often □ Always	□ Often □ Always
For the identical base case, if there is a medium flow of traffic, will you attempt to get into that bus?	□ Never □ Rarely □ Sometimes □ Often □ Always	□ Never □ Rarely □ Sometimes □ Often □ Always

**FOB = Foot Over-bridge*

Yielding Behavior

Question	Vehicle to Vehicle Vendor	Pedestrian
At what distance to the vehicle, will you yield or stop before crossing the road (and let the vehicle pass)?	□ <5 ft □ 5 – 7 ft □ 7 – 9 ft □ 9 ft+	□ <5 ft □ 5 – 7 ft □ 7 – 9 ft □ 9 ft+

Aggressive Behavior

Question	Vehicle to Vehicle Vendor	Pedestrian
Do you get annoyed with drivers and hit their vehicles?	□ Never □ Rarely □ Sometimes □ Often □ Always	□ Never □ Rarely □ Sometimes □ Often □ Always
Do you get angry at other road users?	□ Never □ Rarely □ Sometimes □ Often □ Always	□ Never □ Rarely □ Sometimes □ Often □ Always

Crash & Injury History

Question	Vehicle to Vehicle Vendor	Pedestrian
Have you ever experienced near crash events?	□ Yes □ No	□ Yes □ No

Bicycle Questionnaire

Sample of the questionnaire survey form (Only includes questions used in the study):

<u>Demographic Information</u>

Gender: ☐ Male ☐ Female ☐ Transgender ☐ Prefer not to say

Age: ☐ <18 ☐ 18 – 25 ☐ 25 – 35 ☐ 35 – 50 ☐ 50 – 60 ☐ 60 – 65 ☐ > 65

Education:	
☐ Illiterate	☐ Secondary (Includes Trace Certificate/SSC Vocational)/ Dakhil
☐ No formal education	☐ Higher Secondary (Includes 2 years of 4year Diploma in Engineering & Nursing, HSC Vocational)/ Alim
☐ Drop-out from Primary level education	☐ Diploma/Vocational (Not a Bachelors, similar to Associates)
☐ Primary/ Ibtedayi	☐ Graduate / Fazil
☐ Drop-out from Secondary level education	☐ Postgraduate / Kamil

Monthly Income (BDT)

☐ 5-10k
☐ 10-15k
☐ 15-20k
☐ 20-25k
☐ 25-30k
☐ 30-35k
☐ 35-40k
☐ 40k+

Current Profession:

☐ Government Employee
☐ Private Employee
☐ Self-employed (business)/ Freelance
☐ Garment Worker
☐ Student
☐ Teacher
☐ Doctor
☐ Engineer
☐ Other: ____________________

Bicycle Trip Information

Which type of bicycle do you own?

Do you always/sometimes/never wear safety gears while riding bicycle?

Safety Gears	Frequency of use				
	Never	Sometimes	Often	More Often	Always
Helmet					
Knee Pads					
Reflector					
Elbow pads					
Retroreflective clothing					
Light color clothing					
Panniers or other storage system					
Rear view mirror					
Security lock					
Bell/Horn					
Kick Stand					

Commercialized Bicyclists Trip Information

Bicycle Ownership in case of commercialized use:

☐ Personal ☐ Company provided ☐ Rental

Which company do you serve for?

Type of item carried on bicycle: *(NB: Multiple answers may be applicable)*

☐ Food
☐ Clothes
☐ Grocery items
☐ Newspaper
☐ Crockeries
☐ Other: ____________________

Quantity of the item that are being carried in each trip:

☐ 1-2 kg
☐ 2-3 kg
☐ 3-4 kg
☐ 4-5 kg
☐ >5 kg

What accessories do you use especially for carrying the goods on your bicycle?
(NB: Multiple answers may be applicable)

☐ Handlebar bags
☐ Top tube and frame bags
☐ Messenger bags
☐ Rucksacks
☐ Baskets
☐ Rear back pack
☐ Carrier Rope/ bungies/ tie downs
☐ Other: ________________

How many consecutive shift hours do you prefer for commercialized bicycling?

☐ 3 hours
☐ 3-6 hours
☐ 6-9 hours
☐ > 10 hours

Which location do you prefer for delivering products using bicycle?

Bicyclists' Behavioral Perception

	Never	Rarely	Often	More Often	Always
[redacted].Circulating against the traffic (following wrong way)					
Zigzagging between vehicles while using mixed lane					
[redacted].Handling/ using obstructive objects while riding bicycle (foods, cigarettes)					
Attaining higher speed than required					
[redacted].Having a dispute in speed or race with another cyclist or driver					
Colliding with a pedestrian or another cyclist while cycling					
[redacted].Braking very abruptly on a slippery surface					
Not realizing that a parked vehicle intends to leave and consequently having to brake abruptly to avoid a collision					
[redacted]. Colliding with parked vehicle which suddenly opens door into the path of an oncoming cyclists					
Trying to overtake a vehicle that had previously used its indicators to signal that it was going to turn, consequently having to brake					
[redacted].Misjudging a turn and hitting something in road or being close to losing balance or falling					
.Failing to be aware of road conditions and falling over a bump or hole					
[redacted].Trying to brake but not being able to use the brakes properly due to poor hand positioning					
.Stopping and looking at both sides before crossing a corner or intersection					
[redacted].Circulating under adverse weather conditions					
How often do you get distracted (e.g., using headphones, navigating GPS, talking with other cyclists while cycling)?					
[redacted].Bicycling with cognitive pressure					
To avoid congestion or save time, have you used bicycle on footpaths?					
[redacted]. Do you apply hand signals while cycling?					

NMV Questionnaire

Sample of the questionnaire survey form:

Questionnaire regarding Non-Motorized Vehicle (NMV)

(For motorcyclists, car & bus drivers, pedestrians, NMV drivers)

Sample No. Location Date:

Demographic Information:

1. Gender: □ Male □ Female □ Transgender □ Prefer not to say

2. Age: □ <18 □ 18 – 25 □ 25 – 35 □ 35 – 50 □ 50 – 60 □ 60 – 65 □ ≥65

3. Education:

□ Illiterate	□ Secondary (Includes Trace Certificate/SSC Vocational)/ Dakhil
□ No formal education	□ Higher Secondary (Includes 2 years of 4-year Diploma in Engineering & Nursing, HSC Vocational)/ Alim
□ Drop-out from Primary level education	□ Diploma/Vocational (Not a Bachelors, similar to Associates)
□ Primary/ Ibtedayi	□ Graduate / Fazil
□ Drop-out from Secondary level education	□ Postgraduate / Kamil

4. Monthly Income (BDT):

□ <10k	□ 35-45k
□ 10-15k	□ 45-55k
□ 15-20k	□ 55-65k
□ 20-25k	□ 65-100k
□ 25-35k	□ 100k+

5. Current Profession:

□ Govt. employee	□ Self-employed (business)/Freelance □ Engineer
□ Teacher	□ Garment worker
□ Private employee	□ Student
□ Doctor	□ Other: ____________________

6. Where do you live: __________________________

Safety Perception:

7. How often does your driving/crossing gets hampered by outlaw NMV movement?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very rarely — Very often

8. NMV drivers are often reluctant to give right of way/crossing.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree — Strongly Agree

9. How often does a NMV intercept in your lane?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very rarely — Very often

10. How likely are you to get involved in an alteration after the interception?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely — Very likely

11. You are likely to become impatient with a slow (NMT) driver and indulge in risky overtaking/crossing behavior.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree — Strongly Agree

12. Angered by NMV driver's behavior, you often give chase with the intention of giving him a piece of your mind.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree — Strongly Agree

13. You often deliberately disregard the right of way when a NMV is passing.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree — Strongly Agree

14. You often misjudge speed of oncoming NMV when overtaking/crossing.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree — Strongly Agree

15. You are often irritated with continuous honkings of the NMVs.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree — Strongly Agree

16. How likely are you to disregard traffic rules when there is only NMV movement on the road?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely — Very likely

17. How often do you think NMVs tend to obstruct passenger boarding and alighting at bus stands?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely — Very likely

18. There should be more protection on NMVs from rear-end collision.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree — Strongly Agree

19. How likely are you to 'Race' oncoming NMVs for a narrow or obstructed road?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely — Very likely

20. How likely are you to honk/yell aggressively to move away NMVs from your lane?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely — Very likely

21. NMVs will have a severe impact in case of crashes due to its very light body

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree — Strongly Agree

22. You tend to miss NMV movements on road during night time due to absence of tail-lights.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree — Strongly Agree

Operational Perception:

23. In your opinion which is the **safest** place for NMV stops?

- ☐ Intersections
- ☐ Mid blocks
- ☐ Beside bus stops
- ☐ Junction points of local & arterials
- ☐ Others: ___________

24. Which route will you prefer when you have alternatives while using NMVs?

- ☐ Fastest route
- ☐ Shortest route
- ☐ Relatively safer route
- ☐ Route with NMV exclusive lane

25. Frequency of major NMV trips

- ☐ Daily
- ☐ Several times a week
- ☐ Several times a month
- ☐ Several times a year

26. What is the minimum travel distance that generally prompts you to take an NMV ride?

- ☐ Less than 1 km
- ☐ 1 to 2 km
- ☐ 2 to 3 km
- ☐ 3 to 4 km
- ☐ 4 to 5 km
- ☐ More than 5 km

27. Which pavement hazards do you think hampers NMV movement most?

- ☐ Potholes
- ☐ Manholes
- ☐ Excessive speed bumps
- ☐ Asphalt cracks
- ☐ Others: ___________

Motorcycle Questionnaire

Sample of the questionnaire survey form:

Demographic Information For Rider:

1. Gender: □ Male □ Female □ Transgender □ Prefer not to say

2. Age: □ <18 □ 18 – 25 □ 25 – 35 □ 35 – 50 □ 50 – 60 □ 60 – 65 □ □ 65

3. Education:

□ Illiterate	□ Secondary (Includes Trace Certificate/SSC Vocational)/ Dakhil
□ No formal education	□ Higher Secondary (Includes 2 years of 4year Diploma in Engineering & Nursing, HSC Vocational)/ Alim
□ Drop-out from Primary level education	□ Diploma/Vocational (Not a Bachelors, similar to Associates)
□ Primary/ Ibtedayi	□ Graduate / Fazil
□ Drop-out from Secondary level education	□ Postgraduate / Kamil

4. Monthly Income (BDT):

□ <10k	□ 35-45k
□ 10-15k	□ 45-55k
□ 15-20k	□ 55-65k
□ 20-25k	□ 65-100k
□ 25-35k	□ 100k+

5. Current Profession:

□ Govt. employee	□ Teacher
□ Private employee	□ Doctor
□ Self-employed (business)/Freelance	□ Engineer
□ Garment worker	□ Other: ____________________
□ Student	

6. □ License ______ Years & Total Driving Experience________ Years.

Motorcycle Rider's Trip Information:

7. Reason behind using motorcycle for providing service purpose: (NB: Multiple answers may be applicable)

□ Recreation □ Employment (Regular) □ Part-time Job
□ Others_______________

8. For the major trips, how long (in min) does it take to reach the destination from the origin?
☐ ________________________

9. Frequency of major motorcycle trip:

☐ Daily ☐ Several times a week ☐ Several times a month ☐ Several times a year

10. Trip distance (in km.) during major motorcycle trip:

☐ Less than 5 km ☐ 5 - 10 km ☐ 10-15 km ☐ 15-20 km ☐ Greater than or equal to 20

Riding Perception

11. Pull onto a main road in front of a vehicle you have not noticed or whose speed you misjudged

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Neutral Strongly Agree

12. Fail to notice or anticipate another vehicle pulling out in front of you and had difficulty stopping

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Neutral Strongly Agree

13. Distracted or pre-occupied, you suddenly realize that the vehicle in front has slowed, and you have to brake hard to avoid a collision

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very rarely Very often

14. Not notice someone stepping out from behind a parked vehicle until it is nearly too late

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely Very likely

15. Ride so fast into a corner that you feel like you might lose control

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Strongly Agree

16. Fail to notice that pedestrians are crossing when turning into a side street from a main road.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Strongly Agree

17. Fail to notice that pedestrians are crossing when he/she comets into a mid block

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Strongly Agree

18. Find that you have difficulty controlling the bike when riding at speed (e.g. steering wobble)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Strongly Agree

19. Skid on a speed breaker, wet road or manhole cover, road marking, etc.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely Very likely

20. Following signals

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely Very likely

21. Using indicators at overtaking

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely Very likely

22. Using indicators at turning

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely Very likely

23. Needed to change speed when going around a corner

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely Very likely

24. Near miss to any vehicle

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very rarely Very often

25. Ride so close to the vehicle in front that it would be difficult to stop in an emergency

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Strongly Agree

26. Ride so close to the vehicle in front that it would be difficult to stop in an emergency

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Strongly Agree

Riding Perception

27. Exceed the speed limit (residential/high way : 30/60)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Neutral Strongly Agree

28. Get involved in overtaking with any vehicle

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Neutral Strongly Agree

29. Tendency of avoiding traffic signals

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very rarely Very often

30. Annoyed during the riding time

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely Very likely

31. Frequent lane change

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Strongly Agree

32. Driving through Footpath

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Strongly Agree

33. Driving through wrong side

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Strongly Agree

34. Dropped at the proper destination

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Strongly Disagree Strongly Agree

35. Followed users' direction (If given)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very unlikely Very likely

36.Used to Hard Break

☑ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very rarely Very often

37.What are the infrastructural factors that prevent you from using your motorcycle more frequently?

☐ Lack of motorcycle riding infrastructure (motorcycle lane, shared lane, separated motorcycle lane, shared facility with pedestrian, etc.)
☐ Lack of suitable motorcycle stoppage at destination
☐ Aggressive driving of vehicles and lack of enforcement
☐ Aggressive driving of motorcycles
☐ Fear of vehicle collisions/traffic accident
☐ Others__________

37. Faced risky spots like : (multiple choices acceptable)

☐ Coverless Manhole ☐ Pot holes, rutting, etc

☐ Dangerous slope ☐ Sharp Turnings ☐ Speed Bump ☐ Speed Hump ☑ others______

38.Do you have any accident history in last two years?

☐ Yes ☐ No (if yes then) Number of Crash __________

39.Type of Crash :

☐ With Heavier Vehicles ☐ With Lighter Vehicles ☐ Pedestrian ☐ Bicycle ☐Motorcycle

40.Crash Reason:

☐ Brake Fail ☐ Over Speeding ☐ Turning Hit ☐ Wrong Side ☐ Others____________

41.Have you ever face any harassment during riding?

☐ Yes ☐ No

42.Harrased By :

☐ Own Rider ☐ Pedestrians ☐ Passing Vehicles ☐ Police ☐ Others____________

43.Which type of harassment do you face? (NB: Multiple answers may be applicable)

☐ Verbal harassment
☐ Non-verbal harassment
☐ Physical harassment ☐ Other: _____________________

44.When did the harassment occur?

☐ Morning ☐ Noon ☐ Night ☐ Others____________

45. What measures did you take after being harassed? (NB: Multiple answers may be applicable)
☐ Transportation Mode shift ☐ Modify schedules
☐ Avoid travelling alone ☐ Staying alert
☐ Avoid overcrowded places ☐ None

46.Comment On the harassment issue :_____________

____

47.Govt should take steps like :

☐Proper Traffic Signs

☐Banning the contract based riders

☐Changing policy of the apps
☐Bike lane
☐Dedicated Bike stand
☐Mandatory Tracking systems

48.Speed Limitation should be in Localities (km/hr) :

☑ 20-30 ☐30-40 ☐ 40-45 ☐ 45-50 ☐ 50+

49.Speed Limitation should be in Highways (km/hr) :

☑ 30-40 ☐40-45 ☐ 45-50 ☐ 50-60 ☐ 60+

50.Dedicated Bike lanes should be in :

☑ Highways ☐Localities ☐ Every where ☐ No need ☐ 50+

51.Bike's Lane should be :

☑ In the middle of the roads ☐Left side of the roads ☐ Right side of the roads ☐ No need ☐ in the middle of each lanes

52.Govt should ban license if :

☑ Passengers without helmet ☐Bike without brake ☐Lower stroke engine motorcycle on highways ☐ Over speeding ☐ Riding without light at night

53.At the turnings there should be :

☐ Mirror ☐ Speed Breaker ☐ Road Markings ☐ Signals ☐ Others____________

54. Govt. Should Test Driving Skill after :

☐ Each 3 years ☐ 5 years ☐ 10 years ☐ 15years ☐ Never

55. In localities most risky things :

☐ NMV's ☐ Pedestrian ☐ Turnings ☐ Animals ☐ Child

56.In highways most risky things :

☐ Heavy Containers ☐ Blind Spots of Vehicles ☐ Wet Roads ☐ Night time riding ☐Others_______

57. Traffic police should check :

☐ License ☐ Helmet Quality Standard Label ☐ Seat Quality of Passenger ☐ Bike quality ☐He shouldn't

Information From Surveyor:

1. Gender: ☐ Male ☐ Female ☐ Transgender ☐ Prefer not to say

2. Age: ☐ <18 ☐ 18 – 25 ☐ 25 – 35 ☐ 35 – 50 ☐ 50 – 60 ☐ 60 – 65 ☐ ☐ 65

3. Education:

☐ Illiterate
☐ No formal education
☐ Drop-out from Primary level education
☐ Primary/ Ibtedayi
☐ Drop-out from Secondary level education
☐ Secondary (Includes Trace Certificate/SSC Vocational)/ Dakhil
☐ Higher Secondary (Includes 2 years of 4year Diploma in Engineering & Nursing, HSC Vocational)/ Alim
☐ Diploma/Vocational (Not a Bachelors, similar to Associates)
☐ Graduate / Fazil
☐ Postgraduate / Kamil

4. Monthly Income (BDT):

☐ <10k
☐ 10-15k
☐ 15-20k
☐ 20-25k
☐ 25-35k
☐ 35-45k
☐ 45-55k
☐ 55-65k
☐ 65-100k
☐ 100k+

5. Current Profession:

☐ Govt. employee
☐ Private employee
☐ Self-employed (business)/Freelance
☐ Garment worker
☐ Student
☐ Teacher
☐ Doctor
☐ Engineer
☐ Other: ____________________

6. Quality	Perception				
	Very low	Low	Neutral	Good	Perfect
Bike					
Helmet					

7.

Origin	Destination

8. Trip Duration_______

9. Trip time___________

10. Pick up spot & Its characteristics

Spot	Bike Stand
	☐Yes ☐No

11.

Asking Price	Negotiated Price

12. Bargaining Limit _______tk.

13. Weather

Rainy	Sunny	Cold

14. Overall satisfactions

Very low	Low	Neutral	Good	Perfect

15. App based ☐Yes ☐No
(Used App___________

If Yes :

16. Pick up Time after requesting______

17. Accuracy with the app time

Very low	Low	Neutral	Good	Perfect

18. Cancellation Record & Frequency

____

19. Rider asked about location before arriving ☐Yes ☐No

20. Rider asked for using contract based riding, leaving app request
☐Yes ☐No

21. Any Comments
