TENDENCY OF INTRA-CITY BUS DRIVERS TO USE CELLPHONE WHILE DRIVING USING ORDERED PROBIT MODEL

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The thesis titled "TENDENCY OF INTRA-CITY BUS DRIVERS TO USE CELLPHONE WHILE DRIVING USING ORDERED PROBIT MODEL" submitted by Md. Shihab Uddin, Farhan Ahsan Farabi and Md. Moin Uddin with St. ID: 135451, 145401 and 135450 has been found as satisfactory and accepted as partial fulfillment of the requirement for the Degree, Bachelor of Science in Civil Engineering.

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DECLARATION OF CANDIDATE

We hereby declare that the undergraduate research work reported in this thesis has been performed by us under the supervision of Professor Dr. Shakil Mohammad Rifaat and this work has not been submitted elsewhere for any purpose (except for publication).

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DEDICATION

We dedicate our thesis work to our family. A special feeling of gratitude to our loving parents. In addition, we express our deep gratitude towards our respected thesis supervisor Professor Dr. Shakil Mohammad Rifaat.

We also dedicate this thesis to our many friends who have supported us throughout the process. We will always appreciate what they have done.

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"In the name of Allah, Most Gracious, Most Merciful"

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ABSTRACT

Road crashes due to driver's distraction has become a major concern these days. Cellphone use while driving is considered one of the most pivotal distraction in this regard. To prevent drivers from using cellphone while driving and to reduce injuries in the road crashes, better understanding is needed about the factors that motivates a driver to use cellphone while driving.

This study seeks to identify the contributing factors affecting cellphone use while driving with broad considerations of driver's demographic characteristics, crash history and environmental characteristics using ordered probit model. It also explores how the interaction of these factors will push a driver in using cellphone while driving. Several intra-city bus drivers were questioned about their cellphone use while driving. Factors such as age, type of cellphone,, marital status, number of trips per day and few others were found to be significantly associated with cellphone use while driving.

To gather data questionnaire survey was chosen. 125 intra-city bus drivers were interviewed to gather data at different location of Dhaka city. From four major categories of information 25 factors were selected for modeling and 59 independent variables were used in ordered probit model analysis. 10 significant variables were obtained from the model which have been used to formulate a forecasting equation to predict the tendency of a bus driver's cellphone use while driving.

Keywords: Cellphone use while driving, Ordered probit model, Factors influencing cellphone use.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Driving is a complicated process as it demands simultaneous execution of cognitive, physical, sensory and psychomotor skills. Despite such complications, drivers are found to be engaged in distraction activities. Any activity that demands driver's attention while driving and has the potential to hamper driver's performance and safety is distraction. Distraction could be like listening radio or music, reading books, eating foods or drinking coffee etc. These distractions occur due to driver's inattention to driving. Secondary task while driving could split driver's attention from driving which lead to distraction. In this study the focus will be on distraction due to cell phone use while driving.

With the advancement of technology, wireless communication is being more and more involved with regular human life and distraction due to cell phone use while driving is very common now-a-days. Driver’s distraction while driving has become a worldwide problem. It has been found that 85% of American drivers use cell phone while driving (Goodman et al., 1999). Lamble et al. (2002) found from a study that two-third of Finnish drivers use cell phone while driving. This tendency of drivers of using cell phone while driving increases risk of road accidents. Collet et al., (2010a, 2010b) found that using a mobile phone while driving increases the risk of exposure to traffic accidents. Wilson and Stimpson (2010) found that fatalities due to distracted driving increased by 28% from 2005 to 2008 and predicted that more than 16000 additional road fatalities were caused by increasing texting volumes from 2001 to 2007. Another study concluded that using cell phone while driving could increase the risk of collision by four times (Redelmeier and Tibshirani, 1997). Considering the risk, cell phone use while driving has been restricted in several states in America. According to Jacobson et al. (2012), 10 states and the District of Columbia have laws against using hand-held cell phones while driving. Also, text messaging while driving is banned in 39 districts along with District of Columbia. Using a hand-held mobile phone while driving is banned in Australia (Pennay, 2008) and the United Kingdom (Clayson, 2007).

In Bangladesh, road accident has become a common phenomenon. Fatality rate due to road accident is very high. Around 80 persons die here every day due to traffic accidents (Maniruzzaman and Mitra, 2005). According to World Health Organization, estimated road traffic death rate per 100000 population in Bangladesh is 13.6% (Retrieved June 19 2018, from http://gamapserver.who.int/gho/interactive_charts/road_safety/road_traffic_deaths2/tablet/atlas.html). Although no recent study has been found for updated statistics, according to a report by National Committee to Protect Shipping, Roads and Railways (NCPSRR), number of road accidents had increased by 8.6% in 2017 compared to that in 2016 (Retrieved June 19 2018, from (https://www.thedailystar.net/backpage/road-accident-sharp-rise-fatalities-1426999). However, no separate data has been found regarding the effects of driver's distraction in traffic accidents. No study has been conducted about the factors related to cell phone use while driving considering the perspective of the drivers of Bangladesh. Also there is no law regarding cell phone use while driving. As a result, drivers are not careful about safety against distraction caused by cell phone use while driving. Hence this study aims to explore cell phone distraction while driving and find out awareness knowledge of the drivers related to cell phone use while driving. This study will also help in formulating policy to prevent traffic accidents caused by cell phone distraction while driving.

1.2 Objective and Scope of the Study

The main objective of the study is to find out the tendency of bus drivers to use cellphone while driving.

For this purpose, 125 drivers were questioned regarding their cellphone use while driving and through ordered probit modeling significant variables were identified which may influence a driver in using cell phone while driving.

Another purpose of this study was to find out the factors including driver's personal characteristic and previous violation history, road condition which influence cell phone use while driving.

This study will relate driver's personal and environmental factors with his willingness to use cell phone while driving through local driver questionnaire survey. Considering the willingness of driver to use cell phone as a dependent variable, effects of the factors as independent variables will be determined using **Ordered Probit Model.**

1.3 Significance of the Study

As the increasing number of traffic collisions due to driver's distraction has become a major issue in transportation sector, a number of researches has been performed around the world to figure out the influence of cell phone use while driving. But very few researches focused on the factors that provoke cell phone use while driving.

In Bangladesh, however, no study has been executed to find out the factors that might influence drivers to use cell phone while driving. This study will focus on effects of accident history of drivers and other factors on willingness to use cell phone while driving.

1.4 Outline of the Thesis

The thesis is organized into six chapters. Chapter two explores the present research work and chapter three includes the selection of appropriate model for this study from a review of widely-used disaggregate models, such as multiple linear regression model, logit and probit model, multinomial logit model, multinomial probit model , nested logit model and ordered logit and probit model.

Chapter four describes the development and the formulation of the chosen model and the way the data and variables are structured.

CHAPTER TWO

LITERATURE REVIEW

2.1 Theory of Planned Behavior

Whether cell phone use by a driver while driving is intentional or not, can be explained through the Theory of Planned Behavior (TPB) (Ajzen, 2005, 1991).

TPB postulates that an individual's intention mainly determines whether a behavior will be performed or not. The key point of this theory is behavioral intention which, in turn, is influenced by three determinants; attitudes, subjective norms, and perceived behavioral control (PBC). Attitude is one's positive or negative evaluation about performing a particular behavior. Subjective norm reflects an individual's perception of the social expectorations to perform the behavior. PBC reflects an individual's beliefs in his/her ability to be engaged in the behavior may influence behavior directly too. These three components of TPB are influenced by one's behavioral, normative, and control beliefs respectively. More positive attitude and greater perception of normative pressure, but not PBC, can strengthen one's intention to perform a behavior (Walsh, White, Hyde and Watson, 2008).

In a study (Walsh, White, Hyde, and Watson, 2008) it has been found that the TPB accounted for 32% of the variability in intentions to use a mobile phone while driving. Another analysis (Zhou, Wu, Rau, & Zhang, 2009) revealed that the TPB was able to explain 43% and 48% variance in hands-free mobile phone use intention and handheld mobile phone use intention. However, Walsh et al. (2007) suggested that using cell phone while driving is affected by addictive tendency towards using a cell phone.

2.2 Behavioral Willingness

Using cell phone while driving may not be intentional always. Rather drivers may be unintentionally provoked to perform such behavior. This type of unintentional behavior can be explained through Behavioral willingness.

Behavioral willingness (BW), which is the focus of the Prototype/Willingness (P/W) model (Gibbons et al., 1998), is an unintentional component involved in decision making to perform a behavior. A number of concepts of P/W model intersect with the TPB.

In many situations people may find themselves in situations in which behavior itself presents the opportunity to perform. P/W model suggests that in such cases, BW rules over intention.
According to P/W model, positive attitude (with less likelihood of risk), subjective norms (perception that others would perform and would approve one's own participation in particular behavior) and prototype (one's own perception of the type of person who perform the behavior) raise the willingness of an individual to perform the behavior.

2.3 Effect of Gender on Cellphone Use

Although risk of accidents with injuries may slightly vary with male and female drivers, tendency to use mobile phone while driving is different for male and female. A few studies examined the risk for gender difference.

Briem and Hedman (1995) conducted a study built up around simulated driving. There were equal number of male and female participants. They found that under difficult conditions like on a slippery road, male drivers exhibited better control compared to female drivers while driving. Again, Woo and Lin (2001) found that cell phone use has negligible influence on reaction time by gender difference. Laberge-Nadeau (2003) found that men have more tendency to use cell phone than women and women are more likely to wait for a red light signal for making a call while driving. But Márquez (2015) found that women have more tendency to use cell phone while driving.

2.4 Variation of Cellphone Use with Age

Using cell phone may vary from age to age. Older people have physical limitations and more cautious than younger people regarding using cell phone while driving. Again young drivers have a tendency to drive recklessly.

A number of studies examined the influences of age on driving experience with or without cell phone use. It has been found that age may hamper reaction time, detection time, visual scanning, recognition memory, time to dial and answer a phone call etc.

Age range of older and younger drivers varied from study to study. For example, older drivers were categorized by age 65+ (Carr D, et al., 1992), 70-88 (Salvia, Petit, Collet, 2016), Middle-aged drivers were categorized by age 5-35 (Carr D, et al., 1992), 22-44 (Salvia, Petit, Coollet, 2016) and younger drivers were categorized by age 18-21 (Donmez, Boyle, Lee, 2010), 18–25 (Strayer and Drews, 2004).

Several studies shows that cell phone use causes longer reaction time for older drivers was longer than younger drivers (Woo and Lin, 2001; Alm and Nilsson, 1995; McKnight and McKnight, 1993). Alm and Nilsson (1995) observed that young drivers had shorter minimum headway. Shinar (2005) found that older people drove slowly compared to other driver groups and younger and middle-aged drivers performed better in case of maintaining lane position. Besides, Poysti (2005) found that young drivers (18-24 years) experienced hazards eight times more often than older drivers (64+ years) while using a cell phone during driving.

2.5 Occupation and Cellphone Use

Hazard experiences for people from different occupations vary. Some professions require more communication than others. Demand for using cell phone for an owner of a business is certainly different for a student. A person in a leading position may need to stay connected with his/her employees all-time. But a retired person is free of that type of necessity.

In a study conducted on people like owner of a business or farmer, employee, working in a leading position and student, Poysti (2005) found that people in a leading position experience hazards three times more often than retired people due to cell phone use while driving. Bener (2016) also found that people in leading position are more vulnerable to hazards caused by cell phone use while driving.

2.6 Cellphone Use and Presence of Passengers

People are likely to be more careful about using cell phone while driving with passengers. The reason behind it might be people become more aware of safety when there are passengers. Again, young drivers have tendency to drive recklessly.

From a survey, Márquez (2015) found that individuals travelling alone have more tendency to use cell phone while driving than individuals travelling with someone. Roney (2013) found that even when passengers are children, cell phone use by drivers is less frequent but not uncommon. However, in case of teen drivers, Williams et al. (2007) found that teen-age drivers are more susceptible to crash risk in presence of passengers, especially in presence of other teenagers and when the passengers are male.

2.7 Perception of Safety

Perception of safety for using cell phone while driving influences driver’s decision to make or receive a call. If driver is aware about his/her and passengers safety, he/she won't make a call or send s message. A driver who had been fined or faced accident previously, will try to prevent such situations happening again.

In a survey, Marquez (2015) found that individuals who have been fined or have been in accident or almost have been in accident, have higher risk perception and individuals who are fond of risk, have more tendency to use cell phone while driving than others. Nelson et al. (2009) found that when drivers perceive using cell phone to be more risky, they try to avoid making or receiving a call.

2.8 Use of Cellphone While Driving Due to Peer Influence

The use of cellphone while driving may be due to peer engagement and helps increase the risk factor of accidents especially in emerging adults.

In a study conducted by Trivedi (2017) on 212 participants and their 625 peers show that participants with peers who used cell phones while driving were more prone to using cell phones while driving themselves.

2.9 Distraction Due to Approaching Phone Call

A driver may become distracted while receiving a phone call but even the anticipation may cause somewhat distraction to the driver.

Research suggests that expectation of approaching phone calls or messages and impulsivity are fundamentally connected and increase the risks vehicle crashes (O'Connor et al., 2016). A driver expecting an important phone call from a source or friend/family may be distracted even before the phone call is made due to anticipation. He might continuously check their cell phone which results in the distraction.

CHAPTER THREE

METHODOLOGY AND MODEL SELECTION

3.1 Introduction

In this chapter the methodology adopted in this study is discussed. Figure 3.1 shows the steps included in the methodology and represented by a flowchart. Each of the three steps shown will be outlined in detail in the following section. The first step, i.e., model selection being an important part of the methodology, is also described towards the end of the chapter.

3.2 Methodology

As outlined in Figure 3.1, the study methodology is divided into three main steps. These are:

1) Statistical model selection, which will include a review of existing models and the selection of the most appropriate one.

2) General development of model, which will deal with the selected ordered probit model.

3) Application of model, which will involve 3 case studies, all of which will need to be calibrated, evaluated and interpreted.

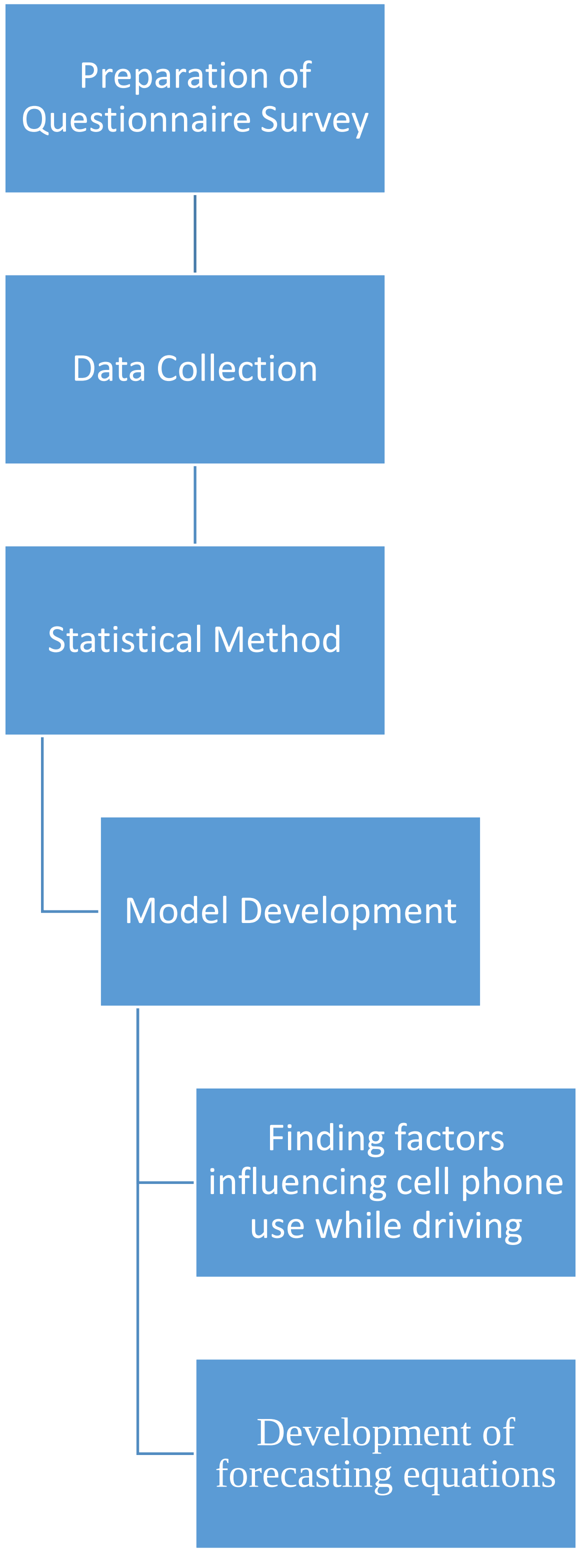

Fig 3.1 Flowchart of methodology

The first step in the methodology is the selection of a statistical model that is suitable for the study. This is done by reviewing different types of statistical models that have been used in traffic accident studies. All of these models are formulated based on varied assumptions. Their applicability depends on the validity of these assumptions. Naturally the wrong choice of a model, because the assumptions are invalid, will lead to biased estimate of the parameters. Before a model is found to be suitable, it is therefore necessary to examine their underlying assumptions as well as their limitations to use.

A number of statistical models have been used in traffic accident analysis. Count models are quite common and these include the Poisson and negative binomial regression models and their zero-inflated counterparts. These are generally applied to accident frequency studies and have not been used in severity analysis. Because the severity level is a discrete outcome, disaggregate models have been used. Some of these include continuous models such as the multiple linear regression; as well as discrete models such as the logit models and probit models. In order to determine which one is most suitable, a detailed review of these disaggregate models will be presented. Among the models reviewed are the multiple linear regression, the binary logit and probit models, the multinomial logit and probit models, the nested logit model and the ordered logit and probit models. The review and the criteria for choosing the most suitable model are described in detail in the next section.

After selecting the most appropriate model, which turns out to be the ordered probit model, the next step is to specify the model to such a detail that it can be used. This involves formulation of the model. In order to complete this, a brief mathematical derivation of the model and the underlying assumptions are included in the discussion.

Furthermore, by examining the structure of the model, and the relationship between dependent and independent variables, a method of estimating the parameters will be described. To verify that the proposed ordered probit model has sufficient explanatory power, a goodness-of-fit test which makes use of the adjusted log likelihood index ratio, $\bar{\rho}^2$ is also suggested. For model calibration, accident data will be required. These are taken from the records of traffic accident in Singapore from 1992 to 2001. The accident record includes crash characteristics and information related to vehicles, road and environmental conditions as well as data on drivers and other road users. From this set of information, the factors for the study will be pre-selected to form the independent variables of the model.

The last step of the methodology is the application of the model to specific severity studies. For the purpose of this research, three case studies have been chosen. They are:

1) two-vehicle crash severity
2) single-vehicle crash severity
3) Pedestrian crash severity.

These case studies are chosen because these types of accident are most common in Singapore. Accident statistics in Singapore shows that two-vehicle crashes form more than half of the total reported accidents while single-vehicle crashes account about one-third of the total road fatality in the country during the considered 10 years' time period. The study of two-vehicle crashes and single-vehicle crashes are useful because these types of crash are given important consideration when designing road layout and road-side safety barriers. For example, these case studies would help decide on proper placement of guardrail so that guardrail not only protects the vehicle from dangerous roadsides but also minimizes crash damages. On the other hand, pedestrian safety should be given more attention since pedestrians are the most vulnerable road users and they are over-represented in fatal and injury crashes in Singapore. A study on pedestrian safety may point to the proper use of pedestrian facilities (e.g., underpass, overhead bridge or pedestrian path).

For each case study an ordered probit model needs to be established. For this purpose, three different data sets are formed. The next task is to get the most parsimonious model, particularly when many variables are considered at the starting of model development. The correlation between chosen variables has been checked to avoid multi co-linearity since faulty sign or implausible magnitudes in the estimated coefficients may come out due to multi co-linearity .The variables included in each model are those that resulted in lower p values of t-test. Adjusted log likelihood index ratio was also considered in the process of omitting variables. Finally, in each case study, the variables having coefficients with appropriate sign showing their tendency to increase or decrease severity is identified. Moreover, the variables contributing to severity may be different for three types of accidents. The significant variables from the model result of each case study are then interpreted and consequently, the possible reasons for each of the factors are then suggested by scientific and engineering judgment. To show how the variation in independent variables would change the different injury probabilities, a reference case is defined for each case study which describes the characteristics of the most typical accident victim. Besides examining single factors, the interaction of these factors is also explored for better understanding of their effects. The detail of model calibration, evaluation and interpretation of each case study are discussed from chapter 4 to 6.

3.3 Statistical Model Selection

A statistical model establishes relationship between a dependent variable and a set of independent variables by the following mathematical expression:

$$Y = f(X) \tag{3.1}$$

where the dependent variable Y is a function of independent variables X .

In traffic accident prediction studies, the outcome variables may be total annual traffic accident frequency or traffic accident rate while in accident severity studies, they may represent the injury of the most severely injured occupant of vehicle, the injury of driver or the injury of pedestrian. Other variables that are thought to provide information on the behavior of the dependent variable are incorporated into the model as predictor or explanatory variables. In accident severity studies, the independent variables may be formed from driver's characteristics, pedestrian characteristics, vehicle characteristics, road features, crash characteristics as well as environmental conditions.

A variety of statistical approaches have been applied in studying accident severity. Many of the above analysis methods were applied by aggregated count of data. A simple approach has been followed by Milliaris et al. (1996) who used the mean and variance of specific factors such as different crash types, vehicle types and restraint use to compare their effect. Another simple approach was employed by Mercer (1987) who examined the correlation between accident severity level and the factors of interest (e.g., restraint device use) to identify the factors significantly contributing to specific severity levels. Cross-tabulation methods have also been used by Brorsson et al.(1993) and Holubowycz et al.(1994) to compare the distributional difference between different groups(e.g., gender and age) and accident severity levels to identify high risk groups(i.e., those that have greater risk of being involved in a certain severity level). Multivariate analysis techniques have been undertaken by Shao (1987) to identify a set of variables that can be used to distinguish accident severity levels. Lassarre (1986) have employed multivariate time-series approaches to develop predictive model of accident severity. Evans (1986) employed a double-pair comparison approach to examine how occupant characteristics affect fatality risk.

However, the disadvantage of using the above approach which relies on aggregate data is that a lot of valuable information is disregarded in establishing relationships between accident severity and contributing factors. This problem is overcome by using disaggregate models. Disaggregate models not only include the capability of testing a broad range of factors that influence accident severity but also it has the capability of capturing powerful disaggregate information about how individual factors influence accident severity. As a result, disaggregate models can lead to more detailed and meaningful findings in accident severity study.

3.3.1 Review of Different Disaggregate Models

Seven disaggregate models are reviewed. The assumptions, limitations and the suitability of these models in accident severity studies are discussed below.

3.3.1.1 Multiple Linear Regression Model

In multiple linear regression model, the link function between the dependent variable and the independent variable is

$$\mathbf{Y} = \boldsymbol{\beta}\mathbf{X} + \boldsymbol{\varepsilon} \tag{3.2}$$

where $\mathbf{Y}$ is an $N \times 1$ response vector in which N is the total sample size, $\mathbf{X}$ is an $N \times (p+1)$ matrix of explanatory variables in which p is the total number of explanatory variables, $\boldsymbol{\beta}$ is a $(p+1) \times 1$ vector of parameters, $\boldsymbol{\varepsilon}$ is an $N \times 1$ random vector whose elements are assumed to be independently identical and normally distributed.

The important assumptions of this model are:

a) Linearity i.e. the expectation of the error term is zero (0).

b) Homoscedasticity i.e. the variance of the errors is the same regardless of the value of $\boldsymbol{X}$.

c) Normality i.e. the error is normally distributed and

d) Independence i.e. the observations are sampled independently.

However, multiple linear regression model has several potential limitations when the dependent variable is expressed as binary. First, errors cannot be normally distributed in case of binary dependent variable. Second, the predicted value could possibly be outside the range of 0 to 1 for certain values of predictor variables. This is particularly troublesome if the expected value is interpreted as a probability. Problems are encountered in using binary dependent variable in multiple linear regression model which was also identified by Khattak and Knapp (2001) when they developed model on injury occurrence. The dependent variable of their analysis was dichotomous (i.e., no crash injury and crash injury). They considered that multiple linear regression model was inappropriate when the dependent variable is dichotomous because it might estimate unrealistic probabilities, i.e., values outside 0 to 1 range.

3.3.1.2 Logit Model and Probit Model

The problem of unrealistic probabilities in the multiple linear regression model can be overcome by specifying a nonlinear model relating $\mathbf{x}_i$ to the probability of an event. Noting that the multiple linear probability model can predict values of $\Pr(y_i = \frac{1}{\mathbf{x}_i})$ that are greater than 1 or less than 0, Aldrich and Nelson (1984) suggested that a sigmoid –shaped relationship between the independent variables and the probability of an event addresses the problem with the functional form in this model. To eliminate this problem, $\Pr(y_i = \frac{1}{\mathbf{x}_i})$ is transformed into a function that range from $-\infty$ to $+\infty$. By choosing functions of $\mathbf{x}_i\boldsymbol{\beta}$ that range from 0 to 1, different probability models can be constructed. Cumulative distribution functions (cdf) have this property. The logistic cumulative distribution function creates the logit model while cumulative distribution function for the standard normal distribution results in the probit model. The final form of the logit and probit model are given below respectively:

$$\ln \frac{\Pr(y_i = \frac{1}{\mathbf{x}_i})}{1 - \Pr(y_i = \frac{1}{\mathbf{x}_i})} = \mathbf{x}_i\boldsymbol{\beta} \qquad (3.3)$$

$$\Pr(y_i = \frac{1}{\mathbf{x}_i}) = \int_{-\infty}^{\mathbf{x_i}\,\boldsymbol{\beta}} \frac{1}{\sqrt{2\pi}} \exp(-\frac{t^2}{2})dt \qquad (3.4)$$

However, the normal and the logistic distribution have similar shapes. For this reason, probit and logit models are very similar. There is no compelling reason to prefer one model over another on substantive or theoretical ground. However, in practice the logistic distribution may be preferred due to the simplicity of probability distribution and density functions.

In case of accident severity studies, the logit model is preferred because of its ease in interpretation in terms of log-odds ratio which probit model cannot do since probit model has no simple closed-form expression for the odds-ratio. Though logit model is applied, named as logistic regression model in different severity studies (Jones and Whitfield, 1988; Lui et al., 1988; Shibita and Fukuda, 1994; Simoncic, 2001), it can account only two states of the severity of injury.

3.3.1.3 Multinomial Logit and Multinomial Probit Model

The multinomial logit model extends the logit model to more than two states. For the nominal dependent variable the multinomial logit (MNL) model(McFadden, 1973) is the most widely used discrete choice model due to its simple mathematical structure and ease of estimation. This discrete choice model is based on the principle that an individual chooses the outcome that maximizes the utility gained from that choice. Based on this principle and the assumption that the error term is generalized extreme value (GEV) distributed, McFadden (1981) derived the simple multinomial logit model. The final form of the model is as follows:

$$P_n(i) = \frac{\exp[\boldsymbol{\beta}_i \mathbf{X}_n]}{\sum_I \exp[\boldsymbol{\beta}_I \mathbf{X}_n]} \qquad (3.5)$$

where $\Pr_n(i)$ is the probability of individual n having alternative i in a set of possible choice categories I, $\mathbf{X_n}$ is a vector of measurable characteristics that determine alternative i; $\boldsymbol{\beta}_I$ is a vector of statistically estimable coefficients .

However, the multinomial logit model has the limitation of independence of irrelevant alternatives (IIA) (Ben-Akiva and Lerman, 1985), such that the odd of m versus n is not affected by other alternatives, i.e.

$$\frac{\Pr(y = \frac{m}{\mathbf{x}})}{\Pr(y = \frac{n}{\mathbf{x}})} = \exp(\mathbf{x}\ [\beta_m - \beta_{\mathrm{n}}]) \qquad (3.6)$$

This expression is only a function of the respective utilities of alternatives m and n, and is not affected by the introduction/removal of other alternatives. This analytical feature implies that the relative shares of the two given alternatives are independent of composition of the set of alternatives.

The limitation of independence of irrelevant alternatives in multinomial logit model was also identified by Shankar, Mannering and Barfield (1996), Chang and Mannering (1999), Lee and Mannering (2002) in their studies on accident severity. Shankar et al. (1996) classified severity of an accident to be one of four discrete categories: property damage, possible injury, evident injury and disabling injury or fatality. But according to them, property damage and possible injury accidents may share unobserved effects such as internal injury or effects associated with lower-severity accidents. However, the basic assumption in the derivation of the multinomial logit model is that error terms or disturbances are independent from one accident severity category to another. Shankar et al. (1996) suggested that if some severity categories share unobserved effects (i.e. have correlated disturbances), the model derivation assumptions are violated and serious specification errors will result.

On the other hand, according to Long (1997), a significant advantage of the multinomial probit model is that the errors can be correlated across choices, which eliminates the IIA restriction. However, computational difficulties make the multinomial probit model impractical.

3.3.1.4 Nested Logit Model

Though multinomial logit (MNL) model is the most widely used choice model due to its simple mathematical structure and ease of estimation, it imposes the restriction that the distribution of the random error terms is independent and identical over alternatives. In this circumstance, the most widely known relaxation of the multinomial logit model is the nested logit (NL) model, which does away with the IIA property by recognizing the existence of subgroups or clusters within the I choice states. McFadden (1981) derived the nested logit model from utility maximization under an assumed generalized extreme value (GEV) distribution of the random disturbances. Using the GEV distribution, the choice probabilities can be written in the following nested logit form:

$$P_n(i) = \exp[\boldsymbol{\beta}_i \mathbf{X}_n + \Theta_i L_{in}] \Big/ \sum_I \exp[\boldsymbol{\beta}_i \mathbf{X}_n + \Theta_i L_{in}] \quad (3.7)$$

$$P_n(j \mid i) = \exp[\boldsymbol{\beta}_{j|i} \mathbf{X}_n] \Big/ \sum_J \exp[\boldsymbol{\beta}_{j|i} \mathbf{X}_n] \quad (3.8)$$

$$L_{in} = \ln[\sum_J \exp(\boldsymbol{\beta}_{j|i} \mathbf{X}_n)] \quad (3.9)$$

where $P_n(i)$ is the unconditional probability of an individual n having alternative i, $P_n(j|i)$ is the probability of an individual n having alternative j conditioned on the alternative category i, J is the conditional set of alternatives set(conditioned on i) and I is the unconditional set of alternative categories, L_{in} is the log sum which is interpreted as the expected maximum value of the attributes that determine alternative probabilities in alternative category i, Θ_i is an estimable coefficient which must have a value between 0 and 1 to be consistent with the model derivation.(see McFadden 1981) .

Several studies related to accident severity are found where the nested logit model has been applied (e.g., Shankar, Mannering and Barfield, 1996; Chang and Mannering, 1999; Lee and Mannering, 2002). Considering the same unobserved effects shared between some of the severity types, Shankar et al. (1996) formed a subgroup or cluster by property damage and possible injury in their study. The structure of the nested logit model eliminates the adverse consequences of shared unobserved effects because logit models determine probabilities using the difference in functions defining severity. Thus, according to Shankar et al. (1996), when a logit nest contains only those severity levels that share unobserved effects, the unobserved effects will be cancelled in the process and thereby preserve the assumption of independence needed to derive the model.

Though nested logit model can overcome the limitation of IIA properties of multinomial logit model, it neglects the ordinal nature of categorical dependent variable. Furthermore, both multinomial logit and nested logit model requires estimation of more parameters in case of three or more alternatives; thus reducing the degrees of freedom available for estimation.

3.3.1.5 Ordered Probit Model

When the dependent variable is ordinal in nature, it should not preferably be treated as nominal. Multinomial and nested logit model cannot handle ordinal dependent variable. Consequently, there will be loss of efficiency due to information being ignored. One way to deal with this problem is to use ordered probit model instead of multinomial logit and nested logit model. The ordered probit model discerns unequal differences between ordinal categories in the dependent variable (McKelvey and Zavoina, 1975; Greene; 2000).

The ordered probit model is usually motivated in a latent (i.e., unobserved) variables framework. The general form of the model is

$$y_i^* = \mathbf{x}_i \boldsymbol{\beta} + \varepsilon_i \qquad (3.10)$$

where y_i^* is a latent, unobservable and continuous dependent variable; $\mathbf{x}_i$ is a row vector of observed non-random explanatory variables; $\boldsymbol{\beta}$ is a vector of unknown parameter; ε_i is the random error term; which is assumed to be normally distributed.

According to Long (1997), the ordered probit model can be derived from a measurement model in which a latent variable y_i^* ranging from $-\infty$ to $+\infty$ is mapped to an observed ordinal variable y. The observed and coded discrete variable y_i^* is determined from the model as follows:

$$y_i = m \text{ if } \tau_{m\text{-}1} \le y^* < \tau_m \quad \text{for } m = 1 \text{ to } M \qquad (3.11)$$

where the threshold values $\tau's$ are unknown parameters to be estimated. The extreme categories, 1 and M, are defined by open-ended intervals with τ_0 = - ∞ and $\tau_M = \infty$. The mapping from the latent variable to the observed categories is illustrated in Figure 2.2 below:

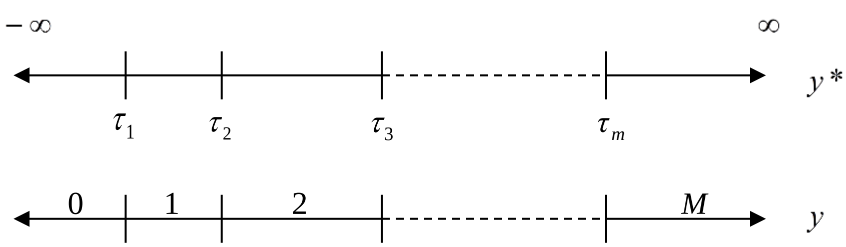

Figure 3.2 Mapping of latent variable to observed variable

However, researchers (e.g., O'Donnell and Connor ,1996; Duncan et al.,1998; Khattak, 2001; Kockelman et al., 2002,Rensky et al., 1999; Quddus et al., 2002) have recognized that the discrete measure of severity is ordinal in nature and have applied the ordered probit or ordered logit models to severity studies. The difference between the two models lies in the assumption of errors. O'Donnell and Connor (1996) and Rensky et al. (1999) have further indicated that the results from the ordered probit and ordered logit are similar. However, ordered probit model is preferable because the assumption that the distribution of errors is normally distributed is more likely to be valid.

3.3.2 Selection of Suitable Model

The forgoing discussion clearly indicates that since severity of injury is necessarily ordered, ordered probit model is more appropriate for accident severity studies; therefore it has been chosen for our study. Several recent studies have also recognized ordered model more appropriate in accident severity studies where the severity categories are of ordinal nature (e.g., O'Donnell and Connor ,1996; Duncan et al.,1998; Khattak, 2001; Kockelman et al., 2002,Rensky et al., 1999; Quddus et al., 2002). This model requires no assumptions regarding the ordinarily of the dependent variable, i.e., severity score. It has also several advantages over other disaggregate models being used in accident severity studies. For example, ordered probit model can account for more than two states of severity of injury which logit and probit model cannot do. It can account for both the categorical and the ordinal nature of dependent variable (severity of injury) while in case of multinomial or nested logit or probit models they can only account for the categorical nature of dependent variable. In addition, ordered probit model is not associated with undesirable properties such as IIA or lack of a closed form likely to be found in multinomial logit model and multinomial probit model respectively. When the expected value of severity is interpreted as probability in ordered probit model, the ranges could not be outside between 0 and 1 like multiple linear regression model.

3.4 Data Collection and Sampling

A questionnaire survey was prepared listing all the factors to be considered. The questionnaire is listed below. In the questions with an underline in the answers, the value was written down.

3.4.1 Location of Survey

Survey was done by interviewing drivers at several bus stands in Dhaka city including:

- Mohakhali
- Sydabad
- Jhigatola Bus Stand

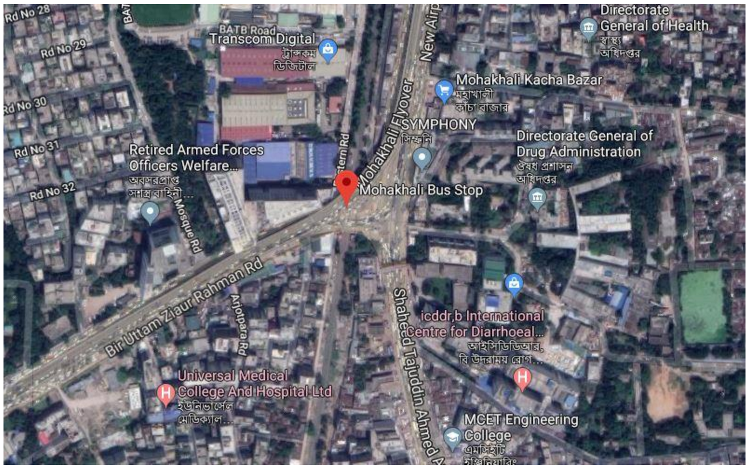

Fig. 3.2 Moakhali Bus Stand Location

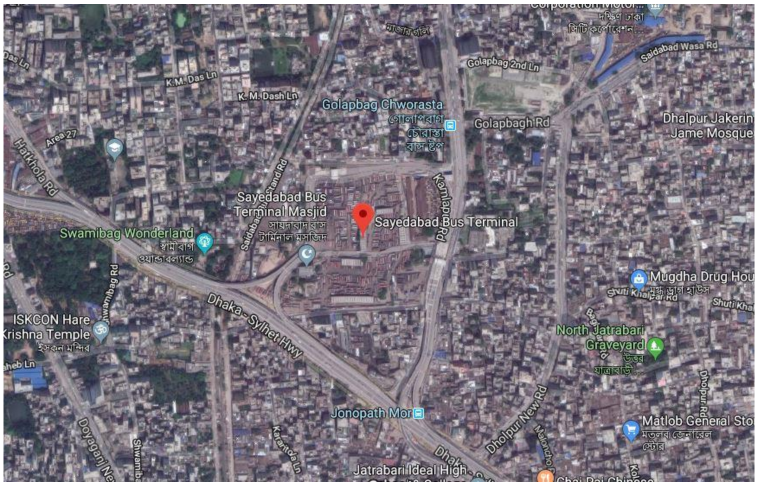

Fig. 3.3 Sydabad Bus Stand Location

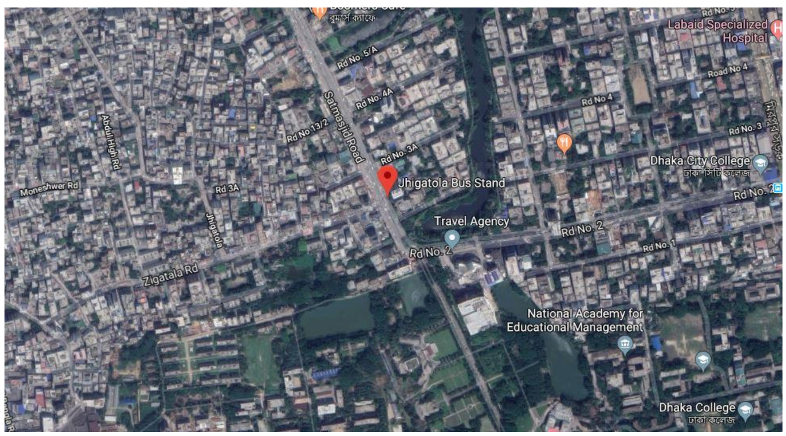

Fig. 3.4 Jhigatola Bus Stand Location

3.4.2 Sample Size

125 Bus drivers were interviewed using a questionnaire survey that was generated by taking local context as well as several reviewed papers into account.

3.4.3 Questionnaire Survey

A questionnaire survey was prepared listing all the factors to be considered. Questionnaire was in English and so was translated into the local language while interviewing for the ease of the participant. The participants were told that they would remain anonymous and only their valueable input is required. The questionnaire is listed below. The questions with an underline in the answers, the value was written down.

3.4.3.1 Questions of Questionnaire Survey

1. Age (Woo and Lin, 2001; Alm and Nilsson, 1995; McKnight and McKnight, 1993):

   >30 31-40 41-50 >50

2. Length of experience: _____

3. Marital Status:

   Married Unmarried

4. No. of Family Members:

5. What type of mobile phone do you use? (Local Context)

   Smart Phone Regular Phone

6. Bus Type:

   A/C Non A/C

7. Income Limit: ____

8. No. of trips per day: ____

9. Hours of driving per day: ____

10. Amount of break time between 2 trips: _____

11. Do you use cellphone while driving? (Local Context)

Never Sometimes Always

12. Talking after stopping vehicle:

Yes No

13. Do you ever Text while driving? (Trivedi et al., 2017)

Never Sometimes Always

14. Do you ever use the Internet while driving? (Local Context)

Never Sometimes Always

15. Do you slow down vehicle when taking a phone call?

Yes No

16. Type of receiving phone call:

Using hand Using headphones

17. Influence of Road surface (roughness of surface, damaged road):

Yes No Sometimes

18. Influence of speed on receiving phone call:

Yes No

19. Do you receive cell phone when stuck in a traffic jam? (Local Context)

Yes No

20. Have you received cell phone in inclement weather? (Rainy, storm, cloudy and dark weather):

Yes No Sometimes

21. Response to caller during night time:

Yes No Sometimes

22. Sources of safety knowledge: (Marquez (2015)

Vehicle Owner BRTA/RHD Radio/TV Newspaper Traffic Police No Source

23. Have you ever been involved in close call situations due to cell phone use? (Korpinen 2012)

YES NO

-If YES, how many times?

1-2 3-5 5<

24. Involvement in traffic collision:

Yes No

-If yes, number of collisions:

1 2 3

25. Involved collision type:

Fatal Serious injury Light injury Property damage

26. Fined due to traffic violation (such as speeding, violating signal, parking, intoxication):

Yes No

3.5 Summary

This chapter has presented an overview of the three steps of methodology for the present research work namely, statistical model selection, general development of model and application of model. In model selection, ordered probit model has been chosen as a suitable model for this study based on the review of different types of disaggregate models. A fuller description and evaluation framework of ordered probit model will be discussed in next chapter.

CHAPTER FOUR

GENERAL DEVELOPMENT OF MODEL

4.1 Introduction

In this chapter, the theoretical framework of the ordered probit model including the model specification and method of evaluation is discussed in detail. The formulation of the ordered probit model explains how the model is employed to fulfill the objective of the study, i.e., to identify the factors affecting usage of cellphone by drivers while driving. The model needs to be calibrated with an accurate and representative dataset. For this reason, database used in this study is also discussed. Finally, to establish a preliminary linkage between cellphone use and the different factors, the most likely factors are presented for further investigation.

4.2 Model Specification

According to Long (1997), the ordered probit model can be derived from a measurement model in which a latent, unobservable, continuous variable y^* ranging from $-\infty$ to $+\infty$ is mapped to an observed ordinal variable y. In our case, y represents the usage of cellphone while driving and can be ordered in three levels (never use cellphone , sometimes use cellphone and always use cellphone) and y^* indicates the tendency to use cellphone. Cellphone use y is thought of as providing incomplete information about the underlying y^* according to the measurement equation:

$$y_i = j \quad \text{if} \quad \tau_{j\text{-}1} \leq y_i^* < \tau_j \qquad \text{for} \quad j = 1 \text{ to } 3 \text{ in our study} \tag{4.1}$$

where the τ's are thresholds or cut points between the intervals. The extreme categories, 1 and 3, are defined by open-ended intervals with τ_0 = - ∞ and $\tau_3 = \infty$.The observed and coded cellphone use variable y is determined from the model as follows

$$y = \begin{cases} 1 \;\; if -\infty \leq y^* < \tau_1 & (Never\ uses\ cell\ phone) \\ 2 \;\; if\ \tau_1 \leq y^* < \tau_2 & (Sometimes\ uses\ Cell\ Phone) \\ 3 \;\; if\ \tau_2 \leq y^* < \infty & (Always\ uses\ Cell\ Phone) \end{cases} \tag{4.2}$$

where τ_1 and τ_2 are yet to be defined cut points separating 3 categories of cellphone use while driving.

The structural form of the ordered probit model taking into account individual observation i (in our case the i^{th} accident) is given by

$$y_i^* = \beta_0 + \mathbf{x}_i \boldsymbol{\beta} + \varepsilon_i \tag{4.3}$$

where $\mathbf{x}_i$ is a row vector of explanatory variables describing characteristics of the driver, road, accident history and the environmental , $\boldsymbol{\beta}$ is a column vector of parameters to be estimated and ε_i is the error term.

The distribution of error term (ε) need to be assumed for maximum likelihood (ML) estimation to estimate $\boldsymbol{\beta}$. For the ordered probit model, ε is assumed distributed normal with mean 0 and variance 1. In this case, the probability density function (pdf) and the cumulative distribution function (cdf) will be respectively

$$\phi(\varepsilon) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\varepsilon^2}{2}\right) \tag{4.4}$$

$$\Phi(\varepsilon) = \int_{-\infty}^{\varepsilon} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt \tag{4.5}$$

Once this distribution of error term is defined, the probability of a particular value of y given $\mathbf{x}$ can be computed. According to following formulation, the predicted probability of any type of injury severity, j for given $\mathbf{x}_i$ is

$$\Pr(y_i = \mathrm{j} \mid \mathbf{x}_i) = \Phi\{\tau_j - (\beta_0 + \mathbf{x}_i\boldsymbol{\beta})\} + \Phi\{\tau_{j-1} - (\beta_0 + \mathbf{x}_i\boldsymbol{\beta})\} \tag{4.6}$$

The model is unidentified since a change in the β_0 intercept in the structural model can always be compensated for by a corresponding change in the thresholds (τ_1 and τ_2) .As suggested by Long (1997), there is an infinite number of parameterizations that could be made to identify the model, only one of two are commonly used that is either β_0 or τ_1 is constrained to 0. The choice of parameters to be used is arbitrary and does not affect $\boldsymbol{\beta}$ or the associated significance tests, as well as the computed probabilities in (4.6). For simplicity, in this study β_0 is set to 0.

The contribution to the likelihood for the i th driver observation depends on which value of cellphone use j is observed. For each of the 3 values of the ordered response, the product over all observations have been taken for which $y = j$ and the likelihood can be written as

$$L = \prod_{i=1}^{n} \prod_{j=1}^{3} \Pr(y_i = j \mid \mathbf{x}_i)^{d_{ij}} \tag{4.7}$$

where d_{ij} =1 if $y_i = j$, and 0 otherwise. Thus, d_{ij} define a set of 3 dummy variables only one of which is equal to 1 for any observation.

Then the final form of the log-likelihood can be written as

$$\ln(L) = \sum_{i=1}^{n} \sum_{j=1}^{3} d_{ij} \ln\left[\Phi(\tau_j - \mathbf{x}_i\boldsymbol{\beta}) - \Phi(\tau_{j-1} - \mathbf{x}_i\boldsymbol{\beta})\right] \tag{4.8}$$

According to Long (1997), the estimation of the model involves maximizing the equation (4.8) using numerical methods (i.e., Newton-Raphson method) to estimate the τ's and the β's .

4.3 Model Evaluation

The important step of model evaluation is to examine the significance of the variables included in the model. Typically, the t-test is used to examine the significance of the coefficients, i.e., $\boldsymbol{\beta}$. Besides this, engineering and intuitive judgments should be able to confirm the validity and practicality of the sign of each covariate and rough magnitude of each estimated coefficient. Furthermore, to evaluate if a model have sufficient explanatory and predictive power, goodness-of-fit measures are then used. It is noted that there is no generally accepted measure of goodness-of-fit for ordered multiple choice (O'Donnell and Connor, 1996; Khattak, 2001). Though there is no generally accepted measure of goodness-of-fit , Kockelman and Kweon (2002), Khattak(2001), Ducan, Khattak and Council (1998), Renski, Khattak and Council (1999), Khattak et al.(2002) and Quddus et al.(2002) have used the log-likelihood ratio index, ρ^2, an informal goodness of fit measure in their studies.

According to Ben-Akiva and Lerman(1985), ρ^2 is given by

$$\rho^2 = 1 - \frac{L(\boldsymbol{\beta})}{L(0)} \tag{4.9}$$

where $L(\boldsymbol{\beta})$ is the log likelihood value of the best fitted model and $L(0)$ is the log likelihood value of the model only with constant term. Everything else being equal, a specification with a higher maximum value of log-likelihood function is considered to be better. The lowest value of log-likelihood function corresponds to the constant term only and is considered the worst case. ρ^2 measure is bounded by 0 and 1. Values of ρ^2 closer to 1 indicate better fit of the model. ρ^2 is similar to the coefficient of determination, R^2, which result from least square regression models (Greene 2000).Like the R^2 statistic, ρ^2 has the undesirable characteristic that for same data set, it will increase when new variables are added to the model. To overcome this disadvantage Ben-

Akiva and Lerman (1985) incorporated a correction factor, K , to give the adjusted log likelihood ratio index as

$$\bar{\rho}^2 = 1 - \frac{L(\beta) - K}{L(0)} \qquad (4.10)$$

where K is the degrees of freedom of the model.

4.4 Cellphone Usage Data

In order to develop ordered probit model that identify the factors affecting the cellphone use while driving a data set is needed that describes the demographic characteristics, environmental factors, vehicle characteristics and crash histories. Data present study was obrained by questioning 160 intra-city bus drivers from Dhaka metropolitan.

4.5 Pre-Selection of Factors

To develop model, it is necessary to pre-select various factors consisting of driver, crash, road and environmental characteristics that could be reasonably expected to influence cellphone use. One way of sorting out these factors is to deliberate upon similar research works where those factors have been used. Subsequently, those factors will form the independent variables for further investigation. Moreover, in most cases, several categorical independent variables can be formed from each of the factors where those variables are mutually exclusive. However, the formation of independent variables from different factors will be described in the subsequent chapters.

The information given in accident record can be classified into four types: driver's socio-demographic information, road related information, environment related information and other information, each of which contains the description of different factors involved in cellphone use while driving. The following sub-sections will designate the factors from these four different types of information.

4.5.1 Factors Selection from Driver's Socio-Demographic Information

The factors associated with the driver's socio-demographic information are shown in Table 4.1. These factors are classified into three categories according to their nature and shown in the first column of Table 4.1. They are driver related factors, driving related factors and accident related factors.

Table 4.1 Factors associated with cellphone usage information

Factors formulated from Socio-demographic information	
Driver related factors	1. Age
	2. Length of experience
	3. Marital status
	4. Number of family members
	5. Type of cellphone
	6. Type of receiving phone call
Driving related factors	1. Income limit
	2. Number of trips per day
	3. Hours od driving per day.
	4. Break time between trips
	5. Texting while driving
	6. Internet use while driving
	7. Talking after stopping vehicle
	8. Slowing down vehicle while receiving call
Crash related factors	1. Traffic collision
	2. Close call
	3. Collision type
	4. Whether fined due to traffic violation
Road related factors	1. Condition of road surface (damaged road etc.)
	2. Influence of speed of vehicle
	3. Use of cellphone during traffic jam
Environment related factors	1. Influence of inclement weather
	2. Influence of night time
Other factors	1. Bus type A.C/Non-A.C Bus
	2. Sources of safety knowledge

4.5.1.1 Driver related factors

Driver related information contains data about driver's age, length of experience, marital status, number of family members and what type of cellphone the driver use. Usage of cellphone while driving varies according to age (Woo and Lin, 2001; Alm and Nilsson, 1995). Several studies shows that cell phone use causes longer reaction time for older drivers was longer than younger drivers (Woo and Lin, 2001; Alm and Nilsson, 1995; McKnight and McKnight, 1993). The other factors were taken into consideration from local context to conduct the study.

4.5.1.2 Driving related factors

Four factors have been found that are driving related. They are income limit of the driver, number of trips per day, hours of driving per day and amount of break between two trips. Poysti (2005) found that people in a leading position experience hazards three times more often than retired people due to cell phone use while driving. So income of driver was considered as a factor to find out if higher or lower income influence the use of cellphone while driving. Drivers who drive vehicle for longer period of time or don't get enough break time may consider using cellphone while driving.

4.5.1.3 Crash related factors

Four crash related factors have been found from crash information. They are whether the driver faced close call situation ever due to cellphone use while driving, involvement in traffic collision ever and whether he had been fined ever for violating traffic rules. Using cellphone while driving could cause distraction. These factors were chosen to find out the awareness of drivers about using cellphone while driving even after facing accident in their driving experience.

4.5.2 Road Related Factors

Three factors are associated with road related information. They are the condition of road surface types, speed of vehicle and traffic jam in road.

Distraction due to cellphone use while driving may increase accident probability. In many studies, different road related factors are found to have effect on accident severity. For example, Chang and Mannering (1998) found that interstate highway accident is more severe that any other types of accident. Renski and his group (1999) indicated in their study of speed limit effect on severity that the highway segments where speed limits were raised by 10 mph resulted in a higher probability of increased severity than those raised by 5 mph. According to the investigation conducted by Shankar and Mannering (1996), when accident occurred on wet pavement with no rainfall the severity of crashes was limited only to property damage and possible injury. So the factors were considered to know whether drivers take road condition into account regarding cellphone use while driving.

4.5.3 Environment Related Factors

Two factors have been found from environment related information: influence of inclement weather and influence of night time.

Different environment scenarios may influence traffic accidents. Duncan, Khattak and Council (1998) reported that injury severity on icy or snowy road conditions was significantly less than that in dry conditions involving truck-passenger car rear-end collisions. According to the investigation conducted by Shankar and Mannering (1996), when accident occurred on wet pavement with no rainfall the severity of crashes was limited only to property damage and possible injury. So whether driver choose to use cellphone in inclement weather and during night time has been considered as factors in this study.

4.5.4 Other Factors

Two other important information that have been considered in this study is the bus type and sources of safety knowledge. Drivers who drive AC bus and who drive Non-AC may not be equally concern regarding cellphone use while driving. Also whether driver have been provided safety knowledge about cellphone use while driving is also an important factor to find out their tendency to use cellphone.

4.6 Summary

This chapter gives an overview at the beginning how the ordered probit model can be employed in our study through model specification and method of evaluation. Subsequently, a brief description of the nature of cellphone use data has been given. These cellphone data contain different factors which may influence a driver to use cellphone while driving.

CHAPTER FIVE

RESULTS AND DISCUSSIONS OF CELLPHONE USE TENDENCY MODEL

5.1 Introduction

In USA distracted driving accounts for approximately 25% of all motor vehicle crash fatalities. In 2015, 391,000 injuries were caused in distracted driving related accidents. Cell phone use is the second largest cause of distracted driving. 14% of distracted driving related deaths comes from cell phone use (as of 2015). Approximately 660,000 drivers use their cell phones while driving during daylight hours, creating a large potential for crashes and fatalities. According to the National Safety Council, cell phone use while driving leads to 1.6 million crashes annually. Drivers are 12.2 times more likely to crash while dialing a phone (https://www.teensafe.com/distracted-driving/100-distracted-driving-facts-and-statistics-2018/). However, the situation isn't clear from the perspective of Bangladesh due lack of data. But the mentioned statistics clearly show the necessity to investigate the factors that influence the drivers to use cellphone while driving.

There have been a good number of studies dealing with the influence of driver's distraction on traffic crash. It has been found that participants engaged in cellphone conversations were more likely to miss traffic signals and reacted to the signals (Strayer & Johnston, 2001). Several studies established that cell phone use hampers the driving performance of younger adults (Alm &

Nilsson, 1995; Briem & Hedman, 1995; McKnight & McKnight, 1993; Strayer, Drews, & Johnston, 2003; Strayer & Johnston, 2001). But very few studies were concerned about the factors which motivate a driver to use cellphone while driving. This study has been conducted to identify the contributing factors with a broad consideration of driver's characteristics, driving characteristics, environmental factors and crash histories.

This chapter describes how the model is set up and calibrated. It includes the description of the data needed for model calibration together with the process of elimination of insignificant variables to get the calibrated model. The model is then evaluated to verify that it has sufficient explanatory power. This is followed by a detailed analysis and interpretation of the significant factors that influence the likelihood of cellphone use while driving.

5.2 Model Calibration

In the chosen ordered probit model, the dependent variable used is cellphone use tendency which may take on one of three values, i.e., never uses cellphone, sometimes uses cellphone and always uses cellphone while driving. The accident is classified based on the worst condition sustained among the casualties.

Not all the factors identified in Chapter 4 are considered in this study. Environment related factors were excluded because drivers were not conscious about inclement weather and night time influence. 25 factors forming 59 independent variables are defined for this study. Some other factors were also excluded because they are found to be statistically insignificant. These include length of experience, number of family members, priority of caller's identity, type of receiving phone call, hours of driving per day, break time between trips, close call situation, traffic collision, whether the driver has been fined ever, influence of speed limit, influence of traffic jam, influence of inclement weather, influence of night time, bus type and sources of knowledge. All 59 variables from 25 factors are retained in the final model. Based on the p-values of the t-tests, 10 variables are found to be significant, i.e. those with p<0.1.

Table 5.1 Explanatory variables used in the model

Explanatory Variables (factors in bold)	Description of the Variables	Mean	Std. Dev.
I. DRIVER RELATED FACTORS			
1.Age			
>30	If age is less than 30 = 1, otherwise=0	0.416	0.495
31-40	If age is 31-40 = 1, otherwise=0	0.416	0.495
41-50	If age is 41-50 = 1, otherwise=0	0.16	0.368
>50	If age is greater than 50 = 1, otherwise=0	0.008	0.089
2.Length of experience			
≤10 years	If experience is ≤10 = 1, otherwise=0	0.544	0.500
11-20 years	If experience is 11-20 = 1, otherwise=0	0.376	0.486
≥20 years	If experience is ≥20 = 1, otherwise=0	0.08	0.272
3.Marital status	If married = 1, otherwise = 0	0.76	0.429
4.Number of family members	Total number of family members of driver's family	5.296	1.704
5.Type of cell phone			
Regular phone	If driver use regular phone = 1, otherwise=0	0.72	0.451
Smart phone	If driver use smart phone = 1, otherwise=0	0.208	0.408
Both regular and Smart phone	If driver use both regular and smart phone = 1, otherwise=0	0.072	0.260
6.Receiving phone call using headphones	If driver uses headphones = 1, otherwise=0	0.168	0.375
II.DRIVING RELATED FACTORS			
7.Income limit			
≤15,000 BDT	If driver earns ≤15,000 BDT = 1, otherwise=0	0.376	0.486
15,001-30,000 BDT	If driver earns 15,001-30,000 BDT = 1, otherwise=0	0.416	0.495
≥30,000 BDT	If driver earns ≥30,000 BDT = 1, otherwise=0	0.208	0.408
8.Number of trips per day			
≤5	If number of trips ≤5 = 1, otherwise=0	0.768	0.424
6-10	If number of trips 6-10 = 1, otherwise=0	0.184	0.389
≥10	If number of trips ≥10= 1, otherwise=0	0.048	0.215
9.Hours of driving per day			
≤8	If hours of driving per day ≤8 = 1, otherwise=0	0.368	0.484
9-16	If hours of driving per day 9-16 = 1, otherwise=0	0.528	0.501
≥16	If hours of driving per day ≥16 = 1, otherwise=0	0.104	0.306

10. Break time between trips			
≤5	If Break time between trips ≤5 = 1, otherwise=0	0.328	0.471
6-15	If Break time between trips 6-15 = 1, otherwise=0	0.136	0.344
16-30	If Break time between trips 16-30 = 1, otherwise=0	0.536	0.501
≥30	If Break time between trips ≥30 = 1, otherwise=0	0	0
11. Texting while driving	If driver does not text while driving = 1, otherwise=0	1.44	0.627
12. Internet use while driving	If driver does not use internet while driving = 1, otherwise=0	1.128	0.380
13. Talking after stopping vehicle	If the driver receives phone call after stopping vehicle = 1, otherwise=0	0.504	0.502
14. Slowing down vehicle while receiving call	If the driver receives phone call while slowing vehicle = 1, otherwise=0	0.328	0.471
III. CRASH RELATED FACTORS			
15. Previous Traffic collision			
No collision	If driver never had any collision previously = 1, otherwise=0	0.44	0.498
1 collision	If driver underwent 1 collision previously = 1, otherwise=0	0.216	0.413
2 collisions	If driver underwent 2 collision previously = 1, otherwise=0	0.184	0.389
≥3 collisions	If driver underwent ≥3 collision previously = 1, otherwise=0	0.16	0.368
16.Previous close calls without accidents			
No close call	If driver never had any close call previously = 1, otherwise=0	0.544	0.501
1-2 close calls	If driver had at least 1-2 close calls previously = 1, otherwise=0	0.288	0.455
3-5 close calls	If driver had 1at least 3-5 close calls previously = 1, otherwise=0	0.104	0.306
≥5 close calls	If driver had ≥5 close calls previously = 1, otherwise=0	0.064	0.246
17. Collison type			
No collision	If driver never had any collision previously = 1, otherwise=0	0.44	0.498
Property damage due to collision	If only property damage occurred due to collision = 1, otherwise=0	0.224	0.419
Light injury due to collision	If light injury occurred due to collision = 1, otherwise=0	0.16	0.368
Serious injury due to collision	If serious injury occurred due to collision = 1, otherwise=0	0.12	0.326
Fatal collision	If fatality occurred due to collision = 1, otherwise=0	0.072	0.260
18. Whether fined due to traffic violation	If driver was fined previously = 1, otherwise=0	0.368	0.484
IV. ROAD RELATED FACTORS			
19. Condition of road surface (damaged road etc.)			
Influenced by road surface	If driver is influenced by road surface = 1, otherwise=0	0.472	0.501
Never influenced by road surface	If driver is never influenced by road surface = 1, otherwise=0	0.32	0.468
Sometimes influenced by road surface	If driver is sometimes influenced by road surface = 1, otherwise=0	0.208	0.408
20. Influence of speed of vehicle	If driver is not influenced by speed of vehicle = 1, otherwise=0	0.256	0.438
21. Use of cellphone during traffic jam	If driver does not uses cellphone during traffic jam = 1, otherwise=0	0.208	0.408
V. ENVIRONMENT RELATED FACTORS			
22. Influence of inclement weather			
Influenced by inclement weather	If driver is influenced by inclement weather = 1, otherwise=0	0.232	0.424
Never influenced by inclement weather	If driver is never influenced by inclement weather = 1, otherwise=0	0.52	0.502
Sometimes influenced by inclement weather	If driver is sometimes influenced by inclement weather = 1, otherwise=0	0.248	0.434
23. Influence of night time			
Influenced by night time	If driver is influenced by night time = 1, otherwise=0	0.328	0.471
Never influenced by night time	If driver is never influenced by night time = 1, otherwise=0	0.328	0.471

Sometimes influenced by night time	If driver is sometimes influenced by night time = 1, otherwise=0	0.24	0.429
Night time is not applicable for cellphone use	If nighttime is not a factor = 1, otherwise=0	0.104	0.306
VI. OTHER FACTORS			
24. Bus type A.C/Non-A.C Bus	If the bus is Non-A/C = 1, otherwise=0	0.968	0.177
25. Sources of safety knowledge	The source from which the driver received traffic knowledge	2.712	1.954

Table 5.2 Results using Ordered Probit Model

Receiving Call	Coef.	z	p> |z|
Age (41-50)	0.546	1.73	0.084
Marital status	-0.452	-1.76	0.078
Type of phone (Regular)	-0.550	-2.07	0.038
Income (>30,000 BDT)	-0.607	-2.13	0.033
Texting while driving	0.641	3.23	0.001
Number of trips (0-5)	-2.048	-2.99	0.003
Number of trips (6-10)	-1.415	-1.94	0.052
Influenced by road surface	-1.063	-3.51	0.000
Not influenced by road surface	-0.840	-2.68	0.007
Influenced by speed	0.442	1.68	0.092

5.3 Model Evaluation

The mean is the average of the all the data of a specific variable and the Standard deviation is the dispersion of a particular data from the mean. For Example, for the driver group within age range 41-50, the mean is 0.16 that means 16% of the sample drivers are within this range and thei deviated by 0.3680813.

5.4 Interpretation of Significant Variables in the Model

Of the 25 factors, 10 variables were found to be statistically significant. They are categorized below.

5.4.1 Driver Characteristics

Seven driver factors were investigated in this study: age, length of experience, marital status, number of family members, type of phone use, and type of receiving phone call. Of these, three were found to be significant in the model. They are: age, marital status and type of phone use.

For the purpose of comparison, drivers were divided into four age groups (<30, 31 to 40, 41 to 50, >50 years old). Of these age group, only the age group, 41 to 50 was found to be significant with co-efficient value (0.5462387). This shows that this age group is vulnerable towards using cell phone while driving and are more inclined to do so.

The marital status of the driver was found to be significant with the co-efficient value of (-0.45299). Which means that those who are married tend to use less cellphone while driving than married drivers.

The type of phone was divided into three categories: Regular phone, Smart phone and using both regular and smart cell phones. Of these variables, only regular phone was found to be significant with a co-efficient value of (-0.5504228) which shows that those who use regular cell phones, tend to use their cellphone less while driving.

5.4.2 Driving Characteristics

Six factors were studied in this study: Income limit, number of trips per day, hours of driving per day, break time between two trips, texting while driving, internet use while driving, stopping while

receiving cell phone and slowing down while receiving cell phone. Of these, only income and texting while driving was found to be significant.
Income was divided into three categories. They are (>15,000, 15,001-30,000 and >30,000 BDT). Only the group with income (>30,000 BDT) was found to be significant with a co-efficient of (-0.6079782) which shows that when income exceeds 30,000 BDT, driers tend to use cellphones less while driving.

Texting while driving was found to significant with a co-efficient value of (0.6410435) which shows a positive significance meaning, those who text while drive are more inclined to use cellphones for receiving phone calls while driving.

The number of trips per day of the driver was divided into three categories: (>5, 6-10 and <10). Of these, the groups of (>5 and 6-10) showed negative significance with co-efficient values of (-2.048956 and -1.415299) with those who undergo (0-5) trips using more less cellphone while driving.

5.4.3 Road Characteristics

Among the factors associated with road conditions, one was found to be significant- the road surface condition. Three factors were find out: Road surface condition, influence of speed and influence of traffic jam on using cellphones while driving.

Road surface condition was divided into two variables. Drivers who considers road surface condition while driving and drivers who does not consider road surface while driving. Both proved to be significant with values (-1.063482 and -0.8401736) respectively with drivers who considers road surface proving to be more inclined to use cell phones while driving.

Influence of speed was found to be significant in this study with a positive co-efficient value of (0.4420713) showing that if the speed is high the driver tends to use less cellphone but the tendency increases as the speed decreases.

5.5 Forecasting Equation

Using the co-efficient of the significant variables and ordered probit model, a forecasting equation was develops in the form of y=f(x). The forecasting equation is:

$$y = \beta_{agefortyonefifty} \times x_1 + \beta_{maritalstatus} \times x_2 + \beta_{mamobileregularphone} \times x_3 + \beta_{incomethirtyup} \times x_4 + \beta_{textdrive} \times x_5 + \beta_{tripszerotofive} \times x_6 + \beta_{tripssixtoten} \times x_7 + \beta_{roadsurfaceyes} \times x_8 + \beta_{roadsurfaceno} \times x_9 + \beta_{speedinfluence} \times x_{10}$$

$$y = 0.546x_1 - 0.453x_2 - 0.550x_3 - 0.608x_4 + 0.641x_5 - 2.049x_6 - 1.415x_7 - 1.06x_8 - 0.840x_9 + 0.442x_{10}$$

The forecasting equation will categorize a driver into a group by assigning any of the three numbers (1=Never receives phone call, 2 = Sometimes receives phone call, 3 = Always receives phone call). By putting the values of different significant variables in the equation, the y value for a driver can be obtained.

5.6 Summary

In order to identify the factors affecting cellphone use while driving, a variety of factors were studied that can influence the cellphone use tendency while driving. This study suggests that the age of driver, marital status, type of phone uses by driver, income limit, number of trips per day, road surface condition and speed of bus play a major role on influencing the tendency of a driver to use cellphone while driving.

CHAPTER SIX

DISCUSSION AND CONCLUSION

6.1 Introduction

The objectives of this study are to identify the factors affecting the use of cellphone while driving and developing a forecasting equation to predict the cellphone use of a driver while driving. To achieve these objectives, various factors from driver characteristics, driving characteristics, road conditions, crash histories, and environmental characteristics have been investigated. Ordered probit model has been used for statistical analysis to find out the significant variables and their inter-relationship, given the ordinal nature of the cellphone use categories.

This chapter gives an overview of the important findings of this research. This is followed by suggestions for precautionary measures to be taken to enhance safety as well as suggestions for future research.

6.2 Discussion and Recommendation

Driver related information shows the effects from some factors on cellphone use while driving. Among the considered driver related information, it has been found that drivers within age limit forty one to fifty are more vulnerable to use cellphone while driving. Drivers within this age range are mostly married. They have to maintain their family and remain connected with them. This could be a reason of their using cellphone while driving. This study also found that marital status of a driver influence the cellphone use behavior. Married drivers, who put the responsibility of running family on their wives, have to worry less about their family. This might be a reason of married drivers are less susceptible to use cellphone while driving. Type of phone used by a driver also influence the cellphone use behavior. Drivers who use regular are usually from old generation and not interested in technological gadgets. That’s why they might not be so eager to use cellphone while driving.

Driving characteristics of a driver effect the cellphone use while driving. Drivers with income more than BDT 30000 are less willing to use cellphone while driving. From the perspective of Bangladesh, income of a driver increases with his longer experience in the field. For a bus driver in Bangladesh, to earn more than BDT 30000 per month, the driver has to be experienced. And experienced drivers are more careful about their driving. This awareness could lead them to not receive phone call while driving. Texting while driving can be considered as an indicator. Drivers who text while driving are more prone to receive phone call while driving. Number of trips per day can affect the cellphone use behavior. Drivers who take zero to five trips a day are less susceptible to use cellphone while driving compared to the drivers who take six to ten trips per day. Drivers who take more trips, have to stay on road for longer period of time and get less break time. So they might consider receiving phone call while driving.

Road surface condition influence the cellphone use behavior of the drivers. Both categories of driver who consider bad road surface before receiving a phone call or not, are less prone to use cellphone while driving. Those who consider the road surface condition before receiving a phone call, comparatively are less prone to use cellphone while driving than those who don't consider.

No crash histories or environmental factors has been found as significant variables. This scenario shows how less aware the drivers are about using cellphone while driving. Even though most of drivers have faced accidents or close call situation in their experience due to cellphone use, they don't grew conscious later. And also environmental conditions like inclement weather or night time visually can't influence them.

Awareness of the drivers can't be changed overnight. To increase the safety perception of the drivers, most vulnerable driver groups are needed to be identified and training could be provided to them. It should be kept in mind that the model developed for this study was based on data collected by questionnaire survey; therefore, the results of those models largely depend on the accuracy of collected information. This study was limited to the intra-city bus drivers only and could be expanded considering the bus drivers from different districts. Also considering drivers from different vehicles, could provide a full picture of perception of safety of the drivers regarding cellphone use while driving.

6.3 Conclusion

In summary, the present research work has identified the factors affecting the cellphone use while driving using ordered probit model. This work suggests that several factors such as age, marital status, income, texting while driving, type of cellphone, number of trips per month, road surface condition play major roles in affecting the cellphone use while driving. The findings of this study give a basis for developing effective countermeasures to improve road safety perception regarding cellphone use while driving.

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APPENDICES

APPENDIX A

This appendix shows the results and analysis of the ordered probit model in Table A.

Table A   Results and Analysis of the Ordered Probit Model

```
Ordered probit regression                         Number of obs   =        125
                                                  LR chi2(10)     =      56.80
                                                  Prob > chi2     =     0.0000
Log likelihood = -108.01336                       Pseudo R2       =     0.2082
```

receivingcall	Coef.	Std. Err.	z	P>|z|	[90% Conf.	Interval]
agefortyonefifty	.5462387	.315728	1.73	0.084	.0269123	1.065565
maritalstatus	-.45299	.2569228	-1.76	0.078	-.8755904	-.0303896
mobileregularphone	-.5504228	.2658304	-2.07	0.038	-.9876748	-.1131707
incomethirtyup	-.6079782	.285013	-2.13	0.033	-1.076783	-.1391736
textdrive	.6410435	.1983136	3.23	0.001	.3148467	.9672403
tripszerotofive	-2.048956	.6853965	-2.99	0.003	-3.176333	-.921579
tripssixtoten	-1.415299	.7289143	-1.94	0.052	-2.614256	-.2163412
roadsurfaceyes	-1.063482	.3027194	-3.51	0.000	-1.561411	-.5655525
roadsurfaceno	-.8401736	.3133236	-2.68	0.007	-1.355545	-.3248021
speedinfluence	.4420713	.2625403	1.68	0.092	.0102309	.8739117
/cut1	-2.921021	.8607907			-4.336895	-1.505146
/cut2	-1.59925	.8419582			-2.984148	-.2143524