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IDENTIFYING AND QUANTIFYING INFLUENCING FACTORS FOR USING RIDESHARING SERVICES IN DHAKA CITY

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ABSTRACT

Ridesharing service is a new transportation mode in Bangladesh. However, it has already become a popular traveling mode in Dhaka city of Bangladesh. Therefore, the use of some other transportation mode has been decreased. This sudden popularity creates the need to know the influencing factors of ridesharing service and the impact it is creating on other modes. For city planners, it is essential to understand this new mode and incorporate this new mode in the future policies and plans. To understand a new mode it is very important to know why the mode is becoming popular, what are the benefits this mode is providing, whether any specific group of people choosing this new mode etc. This study has attempted to identify the influencing factors of choosing ridesharing services in Dhaka city. To do that a Binary Logit Model has been developed and exploratory data analysis has been done. This study has found that if one wants to travel a longer distance in a short time, he/she prefers ridesharing service and willing to bear the extra money it costs. Car or Bike owners are less likely to use ridesharing service. Generally, young people use ridesharing service more frequently. Businessmen are more likely to use ridesharing service than any other occupation. In sum, young businesspersons while travelling comparatively longer distance are showing highest likelihood to use ridesharing service. This is leading to a conclusion that there is a group of people in Dhaka city who are searching for a more comfortable and faster transportation mode and this group is ready to bear the extra cost. This is indicating a potential market for a more reliable and comfortable public bus service with fewer stoppages to meet their demand.

KEYWORDS: Ridesharing, mode choice, disaggregate modeling, discrete choice, logit model, logistic regression.

1. INTRODUCTION

Ridesharing has become very important transportation trend in the whole world, especially in metropolitan cities. Ridesharing is a service where it offers direct access for its members to a fleet of cars distributed throughout a city or town. It is less costly than having a car and more flexible than traditional car rental services (Sioui, Morency, & Trépanier, 2012). It is also called as carpooling, car-sharing and lift-sharing. It is for sharing journeys of different people so that more than one person could travel together and reduce the use of a vehicle on the street.

The transport system is one of the biggest problems in Dhaka. Going from one place to another is very hard and time-consuming for residents of Dhaka city. According to World Bank, average traffic speed in Dhaka has dropped from 21 km/hour to 7 km/hour over the last 10 years (An updated list of ride-hailing startups In Dhaka, 2017). In 2015, 54800 motor vehicles were sold in which 28500 were passenger cars. That means on average 78 cars were sold per day in 2015 (Knoema, 2018). The rate of buying cars is increasing day by day. This is increasing the traffic congestion in Dhaka.

Ride-hailing apps like Uber, Pathao and others, who provide ridesharing services,have become very popular in Dhaka in recent times. On average, Uber, Pathao and Bahon altogether log in 10,000 rides a day. But a top official of the Bangladesh Road Transport Authority thinks the actual number is higher (Islam, 2017). Pathao's business model has become more popular by offering motorcycles as a mode of transportation for its customers, making them direct competitors of the taxi and CNG auto-rickshaw rental services. It goes without saying motorbikes unlike auto-rickshaws and taxis are not only fast but also easy to avoid traffic jams, making them ideal to navigate Dhaka's traffic-choked roads.

When more and more people are using ridesharing services frequently, everyone is not happy with the expansion of those services. The success of those ridesharing services is making CNG and auto-rickshaw useless. Recently CNG and auto-rickshaw workers' unions called for a 48 hour-strike and called for a ban on app-based transport services, starting from December 27 in both Dhaka and Chittagong. However, the move drew widespread criticism and was withdrawn on December 24 (Mamun, 2017). From this action, we can understand that there are impacts of those ridesharing services on other transport modes of Dhaka city.

This study attempts to find out the factors which are influencing people to use those ridesharing services by replacing other modes of transport. When people are using ridesharing service, some other mode is not used. Like people have reduced using CNG, that is what CNG drivers are saying. So, this study would try to understand what type of impact and on which modes are making those ridesharing services. For doing this study Dhaka is selected as a study area. Dhaka is highly populated, and the density is also very high. Dhaka and Chittagong have ridesharing services. But those services have started their journey in Chittagong recently. People of Chittagong have not adopted as like as the people of Dhaka. Because of this, Dhaka is suitable for this study.

The aim of the study is to identify the factors influencing the use of ridesharing services in Dhaka City. To do that a Binary Logit Model has been developed. The factors, which influence the use of ridesharing services and mode choice in other studies, were identified from the literature. From binary logit model, influencing factors in the choice of ridesharing services have been identified and quantified.

2. LITERATURE REVIEW

This section presents a brief overview on ridesharing along with theoretical concept of mode choice models and factors affecting mode choice.

2.1 Ridesharing services and users

Ridesharing is based on an old idea: sharing an expensive resource to allow many people to use it without anyone assuming the entire financial burden on his own. Ridesharing began in

Switzerland in 1948 and became popular in the early 1990s (Shaheen & Cohen, 2007). In recent years, ridesharing has become a key transportation trend, especially in metropolitan areas where ridesharing services have been growing at an impressive rate. For example, the number of ridesharing users in the world has increased from 0.35 million in 2006 to 4.94 million in 2014 (Prieto, Baltas, & Stan, 2017). The principal of the ridesharing is that an individual gains the benefits of private car though he has no private car on his own along with the maintenance cost of a car (Martin & Shaheen, 2011). The way Uber, Pathao and others provide ridesharing services is a bit different from definition and more like a taxi service. These service providers have registered car owners who are willing to share their rides and those rides are available via respective provider's smartphone app based on proximity. A user can check the availability of rides near him/her and can hail that ride for a rent. Increasing users of smart phone in the last few years have given ridesharing a significant boost. Right now, it is possible to provide better real time match between driver and passenger in terms of time and location. Many studies are focused on the topic of building better algorithms for real time match.

Several studies have been conducted for the estimation of the ridesharing users' potential market (Millard-Ball, Murray, Schure, Fox, & Burkhardt, 2005). Market segmentation based on sociodemographic variables such as age, education or household size may be used to detect the profiles that are the most likely to use ridesharing services. Consequently, knowing the key demographic, behavioral and geographic drivers may help to increase the diffusion of ridesharing services. In a research, existing ridesharing users appeared to be younger and more educated (Burkhardt & Millard-Ball, 2006; Efthymiou, Antoniou, & Waddell, 2013). A research found that ridesharing users were often students and belonged to low-income households (Shaheen, Schwartz, & Wipyewski, 2004). Vine, Zolfaghari, & Polak (2014) summarized the socio-economic profiles of ridesharing users as urban, well-educated, moderate or upper income, younger adults that live alone or in small households without children. Zheng, et al. (2009) showed that willingness to participate in a university community ridesharing system was associated with the respondent's status at the university (i.e., student, professor or administrative staff).

From the above discussion it is clear that ridesharing services have some specific users in a specific place. Mode choice models can identify those users by individual factors. The next section will discuss in details about mode choice models.

2.2 Mode choice

The choice of transport mode is probably one of the most important classic models in transport planning. This is because of the key role played by public transport in policymaking (Ortúzar & Willumsen, 2002). People can select a mode between different travel modes in a typical travel situation. These could be driving, using public transit like bus or rail, walking, riding motorcycle or riding with someone else by sharing the ride. A mode choice or mode split model is concerned with the trip maker's behavior regarding the selection of travel mode (Papacostas & Prevedouros, 2015).The philosophy behind mode choice model is to effectively manage the transport demand and be able to provide for these demands by making changes in the existing system (Minal & Chalumuri, 2014).Traditionally aggregate models are used in dealing with the travel choice behavior of individual travelers. However, the aggregate models have the limitation of forecasting and estimating of travel choice with aggregated zonal data. This led to propose another group of models called disaggregate models. These models require the data that describes the behavior of an individual's characteristics and attitudes towards the travel services provided by each mode (Alraee, 2012).

2.2.1 Factors affecting mode choice

There are some factors, which influences the choice of modes of individuals like type of trip, level of service of different modes or the cost of using a specific mode. The characteristics of the trip also influence the choice of mode (Papacostas & Prevedouros, 2015). Case & Latchford (1981) cited in Yasmin & Maniruzzaman (2008) pointed out two cultural or social aspects as the influencing factors on choice of mode in countries of South East Asia. The first is the status aspect. The second aspect relates to the fear of criminal assault. Therefore, passengers are unwilling to share the vehicle with strangers.

McFadden (1978) had studied the factors influencing the choice of mode. These are:

Variables with Critical explanatory power	• travel cost • on vehicle time • walk time • transfer wait time • transit initial headway • number of persons in household
Variables with important explanatory power	• numbers of transfers • respondent's relation to household head • employment density at work location • suburban or urban • family composition
Variables with ambiguous explanatory power	• household income • residential population density • CBD location with respect to residence • number of workers in household • age of household head • reliability of transportation mode • perception of comfort • safety • Convenience
Variables with low explanatory power	• CBD work location • sex of respondent • age of respondent • work status of household head • general attitudes toward privacy • delay

Papacostas & Prevedouros (2015) had categorized the mode choice behavior of trip makers by three categories. The characteristics of the available modes, the socioeconomic status of the trip maker and the characteristics of the trip. Those are the categories of independent variables that would be included in the mathematical models of mode choice.

2.2.2 Disaggregate (Discrete) mode choice models

The disaggregate approach recognizes the aggregate behavior which is the result of numerous individual decisions and to model individual choice responses as a function of the characteristics of the alternatives available to and socio-economic attributes of each individual. Disaggregate mode choice models have huge advantages over the aggregate models for predicting the consequences of transportation policy measures which affect mode choice. The disaggregate approach explains why an individual makes a specific choice given his or her circumstances and is, therefore, better able to reflect changes in mode choice behavior due to changes in individual characteristics and attributes of alternatives. On the other hand, the aggregate approach rests primarily on statistical associations among relevant variables at a level other than that of the decision maker. As a result, it is unable to provide accurate and reliable result of the change in choice behavior due changes in service or in the population (Ortúzar & Willumsen, 2002; Koppelman & Bhat, 2006).

A proposed framework for the choice process is that an individual first determines the available alternative modes; next, evaluates the attributes of each alternative relevant to the choice under some consideration; and then, uses a decision rule to select an alternative from those available alternatives (Koppelman & Bhat, 2006).

An individual visualizes when selecting a mode, which maximizes his or her utility (Khan, 2007). The utility of a mode is defined as an attraction associated by an individual for a specific trip. Therefore, the individual visualizes when selecting the mode which have the maximum attraction, due to various attributes such as in-vehicle travel time, access time to the transit point, waiting time for the mode to arrive at the access point, interchange time, travelling fares, parking fees etc. This type of hypothesis is known as utility maximization.

The utility is generally represented as a linear function of the attributes of the journey weighted by the coefficients, as a matter of computational convenience, which attempt to represent their relative importance as perceived by the traveler. A possible mathematical representation of a utility function of a mode "m" is shown in Equation (2.1) as,

$$Umi = \beta 1Xmi1 + \beta 2Xmi2 + \ldots\ldots\ldots\ldots + \beta kXmik \qquad (2.1)$$

Where,

Umi is the net utility function for a mode m for individual i;

$Xmi1, \ldots, Xmik$ are k number of attributes of a mode m for individual i; and

$\beta 1, \ldots\ldots, \beta k$ are k number of coefficients (or weights attached to each attribute) which need to be inferred from the survey data.

The choice behavior can be modeled using the random utility model which treats the utility as a random variable, i.e. comprising of two distinctly separable components: a measurable conditioning component and an error component. Therefore

$$Umi = Vmi + \varepsilon mi \qquad (2.2)$$

Where,

Vmi is the systematic component (observed) of utility of a mode m for individual i

εmi is the error component (unobserved) of utility of mode m for individual i

2.2.2.1 Logistic regression based discrete mode choice models

Discrete choice model considers statistical classification technique to classify dependent variable between groups and to calculate each respondent probability to get into one or another group. Discrete choice models based on random-utility maximization are widely used in transportation applications because it has the ability to model complex travel behavior of any population with simple mathematical techniques. There are basically three different types of statistical discrete choice models- Logit model, Probit model and General Extreme Value model. Among these logistic regression based models Logit models are the most popular and widely used because of ease of computation and interpretation.

Binomial Logit Model

When the dependent variable in a study is dichotomous (i.e., ridesharing Service using vs not using), binary logistic regression, as opposed to either multiple regression or discriminant analysis, is particularly appropriate (Hosmer & Lemeshow, 1989). Like multiple regression, binary logistic regression analysis can be used to determine which independent variables and interactions are required to describe satisfactorily attrition or retention. Binary logistic regression analysis also provides predicted probabilities of retention for combinations of the independent variables. Although logistic regression is particularly useful in providing a parsimonious combination of the best predictor variables, such a procedure has the tendency to capitalize on chance sample characteristics (Kerlinger & Pedhazur, 1973).

The logistic regression procedure utilized automatically creates new variables for categorical variables. This obviates the necessity of creating "dummy variables" as in multiple linear regression (Lewis-Beck, 1980). In this study, the coding scheme utilized for the creation of new variables was indicator coding. With indicator coding, the coefficients for the new variables represent the effect of each category compared to a reference category.

2.2.2.2 Model estimation techniques

Among the various estimation techniques used for estimating discrete mode choice models, Maximum likelihood is the most widely used.

Maximum Likelihood Method

Maximum likelihood is the most common procedure used for determining the estimators in binary, multinomial and nested logit models. Stated simply as, "The maximum likelihood estimators are the values of the parameters for which the observed sample is most likely to have occurred" (Ben-Akiva & Lerman, 1994).

There are two important steps in the procedure for maximum likelihood estimation. First one is developing a joint probability density function of the observed sample which is called the likelihood function, and the second one is estimating parameter values that maximize the likelihood function (Ortúzar & Willumsen, 2002). A likelihood function for a sample of 'I' individuals, each with 'M' alternatives are defined as follows:

$$L(\beta) = \prod_{\forall i \in I} \prod_{\forall m \in M} (P_{mi}(\beta))^{\delta mi} \qquad (2.7)$$

Where,

L is the likelihood the model assigns to the vector of available alternatives;

P_{mi} is the probability that individual i chooses alternative m.

δ is chosen indicator (=1 if j is chosen by individual i and 0, otherwise)

The values of the parameters that maximize the likelihood function are obtained by finding the first derivative of the likelihood function and equating it to zero. The most widely used approach is to maximize the logarithm of L rather than L itself. It does not change the values of the parameter estimates because the logarithmic function is strictly monotonically increasing (Alraee, 2012). That's why the likelihood function is transformed to a log-likelihood function and is given as,

$$LL(\beta) = Log(L(\beta)) = \sum_{\forall i \in I} \sum_{\forall m \in M} \delta mi \times \ln (Pmi(\beta)) \qquad (2.8)$$

The first derivative of the logarithm of likelihood function can be represented as shown in Equation 2.9

$$\frac{\partial(LL)}{\partial\beta k} \sum\sum \delta mi \times \frac{1}{Pmi} \times \frac{\partial Pmi(\beta)}{\partial\beta} \forall k \qquad (2.9)$$

The maximum likelihood is obtained by setting Equation 2.9 equal to zero and solving for the best values of the parameter vector, β to insure this is the solution for a maximum value provided that the second derivative is negative definite.

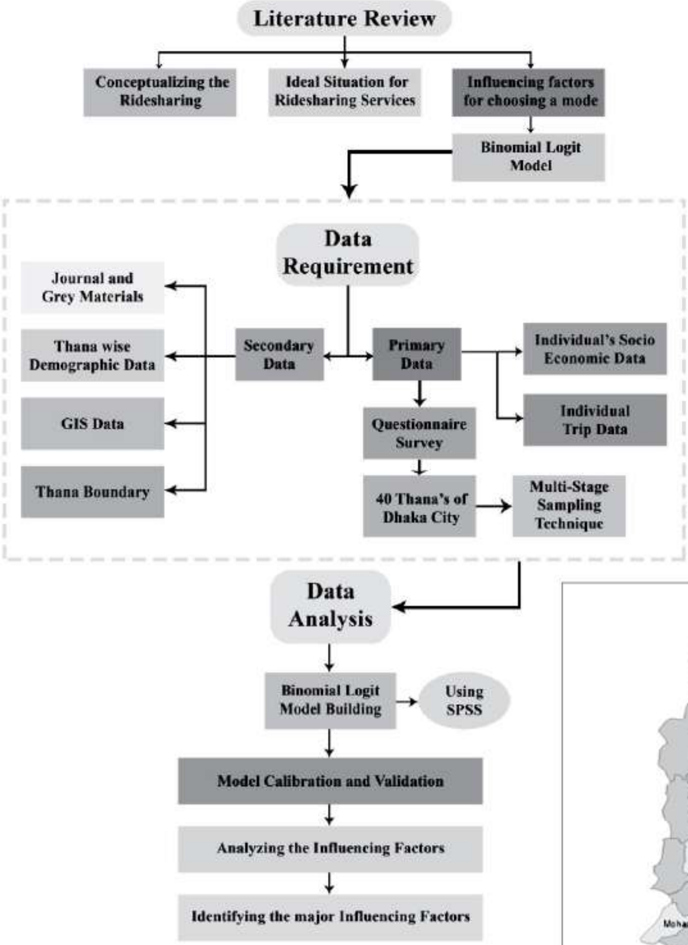
3. METHODOLOGY

In this study binary logit model has been developed to identify and quantify the factors influencing the choice of ridesharing services. Potential factors have been identified from literature review and data on those factors have been collected through questionnaire survey in the study area.

3.1 Study area

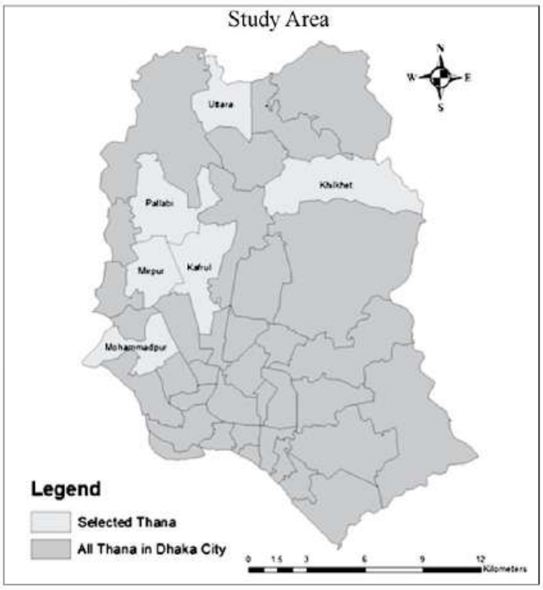
Ridesharing service was introduced in October 2016 in Dhaka city. The study area in this research is Dhaka city, the capital and the largest city of Bangladesh. The population of Dhaka is 14.3 million (BBS, 2011). Dhaka city is divided into two City Corporation. One is Dhaka North City Corporation (DNCC) and the other is Dhaka South City Corporation (DSCC). There are 41 Thana's in Dhaka city. From those 41 Thana's, 6 Thana's were selected based on two online survey on two Facebook pages named "Pathao Users of Bangladesh" and "Uber Users of Bangladesh". These Thanas are the places where the use of ridesharing services is the most frequent according to Facebook polls.

Dhaka city is suffering from severe congestion problem resulting from urbanization and rapid increase of population. It creates a big challenge for transport planners to adopt efficient transport policies to contribute to solution of this problem.



Source : Author, 2019

Figure 1: Working Procedure



Source : Author, 2019

Figure 2: Map of Selected six Thanas in Dhaka

3.2 Data collection

Data collection have been done by household travel survey using travel diaries. The household travel surveys involve contacting respondents in their home and collecting information regarding their household characteristics, their personal characteristics and the travel decisions made in the recent past. Travel diaries are a daily log of all trips including information about trip origin and destination, start and end time, mode of travel, purpose at the origin and destination, etc., made by each household member during a specified time period.

Household questionnaire survey were conducted on 35 households. Number of households from each Thana was selected maintaining the ratio of population according to BBS, 2011. The questionnaire had two sections. The first one had socioeconomic variables (e.g. gender, age, occupation) and the second one had travel characteristics (e.g. car availability, commuting distances, cost, purpose and times). Each household were surveyed for three days. Data were collected for each trip made by the respondent for those three days.

3.3 Model calibration and accuracy assessment

Binomial Logit Model

Binary logistic regression is the method to explore relationship and influence between the dependent binary data and continues or categorical independent variables. Such models are commonly used in many areas of social science and are appropriate when the dependent variable is a simple yes and no decision, the underlying random elements of the distribution are assumed to follow a binomial distribution, and the error terms of the regression follow a logistic distribution (Rodgers & Ghosh, 2001). In this study the dependent variable is going to be 'Yes' for trips used ridesharing service and "No' for trips using other modes except ridesharing service. Our basic logit regression can be expressed as:

$$\log \frac{P1}{(1\text{-}P0)} \quad \beta0+\beta1X1+\beta2X2+...+\beta nXn \qquad (3.1)$$

In this equation P1 is the probability of using ridesharing services and P0 is the probability of not using ridesharing services. β0 is the interception at y-axis, βn is the regression coefficient of Xn, Xn is the predictor variable (Kidanekal & Assefa, 2014). The probability P can be explained by:

$$P(y)= \frac{e^\wedge(\beta0+\beta1X1+\beta2X2+...+\beta nXn)}{1+e^\wedge(\beta0+\beta1X1+\beta2X2+...+\beta nXn)} \qquad (3.2)$$

Here, P(y) is the probability of y occurring. The Odds Ratio can also explain the probability.

3.3.1 Odds Ratio

Odds are the ratio of probability of an event will occur divided by the probability of it will not occur. Mathematically

$$\text{Odds} = \frac{P}{1\text{-}P} \quad \text{where p is the probability of success}$$

Odds always have values greater than zero and if odds value is larger than one it means that success will occur more likely than failure (Kidanekal & Assefa, 2014). For example, odds = 2 means we will observe two success for every one failure and if Odds = 0.5 the reverse will occur. Odds ratio, as the name indicates, is the ratio of two Odds.

$$\text{Mathematically Odds ratio} = \frac{\frac{P1}{1-P1}}{\frac{P2}{1-P2}}$$

Here, P1 and P2 refer to the probability of success in group 1 and group 2 respectively.

If the odds ratio value is greater than one it indicates that the odds of the outcome in group 1 is larger than in group 2. That's why subjects in group 1 are more likely to have success than subjects in group 2. If the odds is ratio less than the value one, expect that the reverse will occur and if it equal to one subjects of odds of both in group 1 and group 2 will equally likely occur. Odds of an event lie between 0 and positive infinity, 1 is the base line for Odds.

3.3.2 Goodness of fit measurement for binomial logit model

Cox and Snell R2 and Nagelkerke R2

Cox and Snell R2 and Nagelkerke R2 statistics provide the geometric mean squared improvement per observation for dichotomous variables. In logistic regression, the r-square measures the amount of variation of dependent variable that is explained by dependent variables.

$$\text{Cox and Snell R2} = 1 - \left(\frac{LL_0}{LL_1}\right)^{\frac{2}{n}}$$

$$\text{Nagelkerke Pseudo R2} = \frac{1 - \left(\frac{LL_0}{LL_1}\right)^{\frac{2}{n}}}{1 - (LL_0)^{\frac{2}{n}}}$$

Cox and Snell R2 value cannot reach to 1 and Nagelkerke R2 improved to reach 1. Nagelkerke R2 value 1 indicate that model is perfect and strong relationship among variable, when the value 0 indicate no relationship among variables.

Classification table

Classification table follow the cross-classification method of dependent variable with categorical variable. The percentage of success is called sensitivity and the percentage of failure called specificity of the model. Classification table given bellow, according to table sensitivity and specificity measured as-

$$\text{Sensitivity} = \frac{d}{c+d}\,(100)$$

$$\text{Specificity} = \frac{a}{a+b}\,(100)$$

Classification table predict the goodness of fit of the model.

Table 1: Classification Table

		Predicted		
Observed		Choice of RS		Percentage Correct
		Do not use RS	Use RS	
Choice of RS	Do not use RS	a	b	$\frac{a}{a+b}(100)$
	Use RS	c	d	$\frac{d}{c+d}(100)$
Overall Percentage				$\frac{a+d}{a+b+c+d}(100)$

Considered for higher sensitivity and specificity value.

Hosmer-Lemeshow test

For binary logistic regression, the format of the data affects the p-value because it changes the number of trials per row. The Hosmer-Lemeshow test does not depend on the number of trials per row in the data as the other goodness-of-fit tests do. When the data have few trials per row, the Hosmer-Lemeshow test is a more trustworthy indicator of how well the model fits the data. It is a goodness of fit statistics, which measure model significance. This follows the chi-square goodness of fit. The method which contain Lower test value indicate good fitting model than higher value.

$$\text{Hosmer-Lemeshow H} = \sum_{v=1}^{10} \frac{(O_n-E_n)^2}{E_n}(100)$$

In the above equation the Hosmer–Lemeshow test statistics, On and On are observed and expected events.

4. RESULTS

To fulfill the aim of the study, a binary logit model has been developed. From the binary logit model the influencing factors have been identified and quantified. The accuracy of the model has been assessed. Variables which was insignificant in the model has been ignored.

4.1 Factors influencing use of ridesharing services

Various factors could influence the adoption of ridesharing services, such as individual and household socio-demographic characteristics, or the characteristics of a trip. However, most of the existing studies on this subject are dominated by descriptive statistics, and therefore have limited ability to disentangle the contribution of various groups of variables to explain choices. This study has explored what factors increase the utility of ridesharing service. Developed model includes some socio-demographic variables and some variables of travel characteristics.

4.1.1 Developing binary logit model

630 trip data were collected from household survey. Three scaler variables (Travel Distance, Travel Time and Travel Cost) and eight Categorical Variables (Age, Gender, Household Income, Private Car Ownership, Motorbike Ownership, Bicycle Ownership, Occupation, and Trip purpose) has been taken as independent variables. Choice of mode has been used as dependent variable, where a value 0 means not using ridesharing services and 1 means using ridesharing services.

Table 2: Binary Logit Model With all Variables

	B	S.E.	Wald	df	Sig.	Exp(B)	90% C.I. for EXP(B)	
							Lower	Upper
Travel Cost	.06	.01	26.09	1	.000	1.06	1.0	1.1
Travel Time	-.18	.04	19.13	1	.000	0.83	0.8	0.9
Trip Distance	.34	.16	4.64	1	.031	1.41	1.1	1.8
Private Car Ownership (No)	6.98	1.34	27.17	1	.000	1071.78	118.5	9690.3
Motorbike Ownership (No)	3.53	1.20	8.70	1	.003	34.28	4.8	246.3
Bicycle Ownership (No)	2.86	2.18	1.72	1	.190*	17.44	0.5	632.0
Gender Female	-.25	.86	.08	1	.771*	0.78	0.2	3.2
Age 45-70			13.13	3	.004			
Age Less than 15	3.70	2.30	2.59	1	.108*	40.56	0.9	1791.0
Age 15-25	4.96	2.38	4.33	1	.037	142.53	2.8	7173.2
Age 25-45	3.72	1.10	11.48	1	.001	41.47	6.8	253.0
Occupation Employee			19.25	3	.000			
Occupation Businessman	6.32	1.48	18.24	1	.000	557.76	48.8	6372.5
Occupation Student	.48	2.27	.04	1	.834*	1.61	0.0	67.3
Occupation Housewife	.46	1.33	.12	1	.728*	1.59	0.2	14.1
Trip Purpose Working			10.60	4	.031			
Trip Purpose Education	-2.33	1.38	2.86	1	.091	0.10	0.0	0.9
Trip Purpose Shopping	1.82	1.56	1.36	1	.244*	6.14	0.5	79.7
Trip Purpose Recreational	-2.13	1.24	2.94	1	.087	0.12	0.0	0.9
Trip Purpose Return to Home	.22	.87	.06	1	.804*	1.24	0.3	5.2
Income 25000-40000			5.21	4	.266*			
Income 10000-25000	-2.70	1.58	2.95	1	.086	0.07	0.0	0.9
Income 40000-65000	-2.28	1.26	3.29	1	.070	0.10	0.0	0.8
Income 65000-80000	-1.59	1.36	1.36	1	.243*	0.20	0.0	1.9
Income Above 80000	-2.49	1.22	4.17	1	.041	0.08	0.0	0.6
Constant	-16.33	3.35	23.75	1	.000	0.00		

*Denotes insignificance at the 90 percent confidence level

From the above model, we can see that some variables are not statistically significant. That means it is better to exclude those variables for the betterment of the model. To exclude insignificant variables we would use Forward Stepwise Likelihood Ratio Method. It inputs variables in a model one by one and when it sees a variable which is not significant enough for the model it excludes that variable from the model. After using this method bicycle ownership, gender and household income have been excluded from the model (table 03).

Table 3: Final Binary Logit Model by using Forward Stepwise Likelihood Ratio Method

	B	S.E.	Wald	df	Sig.	Exp(B)	90% C.I. for EXP(B)	
							Lower	Upper
Travel Cost	.06	.01	23.49	1	.000	1.06	1.0	1.1
Travel Time	-.18	.04	17.43	1	.000	0.84	0.8	0.9
Trip Distance	.32	.14	5.03	1	.025	1.38	1.0	1.8
Private Car Ownership (No)	6.91	1.15	36.08	1	.000	1003.44	105.2	9568.4
Motorbike Ownership (No)	2.67	.84	10.02	1	.002	14.37	2.8	74.9
Age 45-70			19.34	3	.000			
Age Less than 15	4.51	2.21	4.16	1	.041	90.49	1.2	6851.0
Age 15-25	5.70	2.31	6.11	1	.013	300.33	3.3	27709.8
Age 25-45	4.07	.97	17.63	1	.000	58.34	8.7	389.3
Occupation Employee			21.35	3	.000			
Occupation Businessman	5.10	1.14	20.07	1	.000	164.51	17.6	1533.4
Occupation Student	-.77	2.14	.13	1	.718*	0.46	0.0	30.5
Occupation Housewife	-.02	1.32	.00	1	.986*	0.98	0.1	12.9
Trip Purpose Working			11.01	4	.026			
Trip Purpose Education	-2.28	1.26	3.27	1	.071	0.10	0.0	1.2
Trip Purpose Shopping	1.77	1.47	1.45	1	.229*	5.90	0.3	105.9
Trip Purpose Recreational	-1.95	1.12	3.03	1	.082	0.14	0.0	1.3
Trip Purpose Return to Home	.23	.77	.09	1	.766*	1.26	0.3	5.7
Constant	-14.76	2.41	37.63	1	.000	0.00		

*Denotes insignificance at the 90 percent confidence level

4.1.2 Interpreting the model's outputs and identifying influencing factors for using ridesharing services

The above table presents the model coefficients and odds ratio for each factor. The model result indicates that the probability of using ridesharing service is 1.38 times greater when the travel distance increases by 1 km. The probability of using ridesharing services will increase by only 6% for increase of 1 taka travel cost. The probability of using ridesharing services decreases when the travel time increases. Those who do not have private car have the probability of using ridesharing services 1003 times more than who have private car. This clearly indicates that car owners are quite unlikely to use ridesharing services. This actually goes against the general assumption that ridesharing services are going to reduce use of private car, which is true for many cities in the developed world. For Dhaka city, this assumption does not hold its ground. People who are aged in between 15-25 are more likely to use ridesharing services than other age groups. People from the age group of 45-70 are least likely to use ridesharing service. This conforms to the reality because people of these groups are not comfortable of using a smartphone app to call for a ride and they usually take time to get used to something new. Businessmen are 164 times more likely to use ridesharing service than Public or Private Employees. Students are less likely to use ridesharing services than any other occupation. These findings also conform to reality since ridesharing services cost significantly more than public bus service making it obvious that students will not be the frequent user of ridesharing service. In the same ground, it is logical that businessmen, particularly young businessmen who still do not own a car is more likely to use ridesharing service. People use ridesharing service mostly for shopping purpose. However, this information is not statistically significant.

4.1.3 The accuracy of the model

Table 4: Model Summary

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
105.581[a]	0.5	0.801
a. Estimation terminated at iteration number 10 because parameter estimates changed by less than .001.		

From the above table, we can see the Cox & Snell R Square and Nagelkerke R Square values, which are both methods of calculating the explained variation. These values are referred to as pseudo R2 values. The explained variation in the dependent variable based on the model ranges from 50% to 80%.

Table 5: Classification Table

Observed		Predicted		
		Choice of RS		Percentage
		Do not use RS	Use RS	Correct
Choice of RS	Do not use RS	291	6	98
	Use RS	12	59	83.1
Overall Percentage				95.1
The cut value is .500				

Binomial logistic regression estimates the probability of an event (in this case, using ridesharing service) occurring. If the estimated probability of the event occurring is greater than or equal to 0.5 (better than even chance), it classifies the event as occurring (e.g., using ridesharing service). If the probability is less than 0.5, it classifies the event as not occurring. Overall percentage in the above table gives the overall percentage of cases that are correctly predicted by the model. In this case, the accuracy is 95.1%.

Table 6: Hosmer and Lemeshow Test

Chi-square	df	Sig.
8.695	8	0.369

For binary logistic regression, the format of the data affects the p-value because it changes the number of trials per row. The Hosmer-Lemeshow test does not depend on the number of trials per row in the data as the other goodness-of-fit tests do. When the data have few trials per row, the Hosmer-Lemeshow test is a more trustworthy indicator of how well the model fits the data. From the above table we can see the goodness-of-fit test is greater than the significance level of 0.05, which indicates that there is not enough evidence to conclude that the model does not fit the data.

5. CONCLUSION

Ridesharing services is one of the major modes in Dhaka city in recent times. This study has found out the influencing factor for the use of ridesharing service. To identify the influencing factor a binary logit model has been developed. From the binary logit model, influencing factors of ridesharing services have identified and quantified. In Dhaka, if one wants to travel a longer distance in a short time, he/she might use ridesharing service though the service costs extra money. Generally, young people use ridesharing service more frequently. Businessmen are more likely to use ridesharing service than any other occupation. Who have car or bike, is less likely to use ridesharing service. Therefore, the users are typically previous CNG or public transport users. This is leading to a conclusion that there is a group of people in Dhaka city who are searching for a more comfortable and faster transport mode and this group is ready to bear the extra cost. A reliable, more comfortable and faster bus service with fewer stoppages can meet their demand. This indicates that the ongoing bus rapid transit (BRT) initiative can pull passengers from ridesharing services once it is in operation. This study alone can't say that with confidence. To say that further study on impact of ridesharing services on other modes in Dhaka city is required. A stated choice preference based study including this new BRT service can also help for further understanding of the situation.

This study has some limitations in terms of data coverage. If it is possible to conduct this research on a large scale, it can help in transportation policy and planning of Dhaka city. A vast amount of study in the field of transport policy and planning can be conducted by applying the methodology used in this study.

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