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DEVELOPMENT OF MODE CHOICE MODEL BY NESTED LOGIT METHOD IN DHAKA CITY, BANGLADESH

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Abstract: Mode choice behavior is a key element in public transport planning, as it has a direct impact on the design of urban transport system infrastructure, and is also the basis for urban public transport planning and management policymaking. The model is used to analyze and predict the choices that individuals or groups of individuals make in selecting the transportation modes that are used for particular types of trips. Typically, the goal is to predict the share or the absolute number of trips made by mode. An important objective in mode choice modeling is to predict the share of trips attracted to public transportation, this share eventually used in travel demand modeling in its modal split step. This specialized report is prepared using the mode choice model developed under the Dhaka Mass Rapid Transit Development (MRT Line-5 Northern Route) study adopting stated preference (SP) method to estimate the mode choice. Stated preference methods use in the transport sector to grab the preferences in a set of transport modes to estimate the utility functions which is usually used to predict the user's choice of nonexistent transport mode in the urban network before implementation.

Keywords: modal split, discrete choice model, nested Logit, stated preference (SP) survey, value of time (VOT).

1. Introduction

Mode choice is one of the important parameters among others in urban transport planning and design. This is particularly important in planning and designing of new urban mode like MRT, BRT, LRT, etc. and hence to determine the mode share with the introduction of new mode is equally important. In this paper, it is delineated to measure the mode choice model and process of estimation.

Mode choice decision lies on many factors. A proper analysis of the mode choice decisions can help in addressing issues such as forecasting demand for new modes of transportation, mitigating traffic congestion, allocating resources, examining the general efficiency of travel and will provide insight into the travel behavior characteristics. Mode choice analysis is the third step of the classical four step transport planning process, coming after trip generation. Mode choice analysis is the process of

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arriving at a decision about the mode availed of by the public in a particular set of circumstances. Within the travel demand modeling field, mode choice is arguably the single most important determinant of the number of vehicles on roadways. The use of high-occupancy vehicle modes (such as ridesharing arrangements and transit) leads to more efficient use of the roadway infrastructure, less traffic congestion, and lower GHG emissions as compared to the use of single-occupancy vehicles.

In the following sections, first, a literature review is conducted. Then, the study area and the data collection techniques and analyses are described. The study is then followed by the result section that provides models comparison estimated by the new and the traditional choice set formation approaches. Finally, Nested Logit mode choice model for the study area is used to estimate the new mode choice particularly the mass transit mode MRT or BRT which are being implemented in Dhaka city.

2. Literature Review

2.1. Mode Choice Analyses-Background

The choice of transport mode is reasonably the one of the most classic model in transport planning. This is because of the key role played by public transport in policy making (Ortúzar and Willumsen, 2011). With increasing population and urbanization along with prosperous and economic advancement throughout the world, leads to huge demand for mobility. To meet these increased demand, peoples have to make more trips that eventually resulted increasing number of vehicles on the road causes congestion and environment problems. As a consequence, it leads to disrupted traffic conditions like delay, accidents, air pollution and noise pollution incurred huge economic loss on the nation's economy. To relieve such deteriorating traffic condition and mitigate economic loss, one of the probable solution among others is to reduce the number of vehicles from the road by introducing mass rapid transit system. Hence, it triggers the challenge to attract the users of private mods to mass transport modes. Numerous studies have been done to understand the relationship between mode choice and various factors affecting it.

Mode choice modelling is done by means of discrete choice model (Ben-Akiva and Lerman, 1985), the different available alternatives in a discrete choice experiment are mutually exclusive and collectively exhaustive. Discrete choice model is based on selecting the alternative that provides maximum utility to the choice maker. To predict correct mode choice for an individual is not always possible as many unobserved and situational variables come into play for decision making, thus the concept of Random Utility appeared (McFadden, 1980).

The philosophy behind mode choice model is to effectively manage the transport demand and be able to provide for these demand by making changes in the existing system.

2.2. Factors Affecting Mode Choice Behavior

Mode choice of a trip maker is influenced by a wide range of social, economic, cultural and environmental factors, like travel time, travel cost, waiting time, in-vehicle time, access time, availability of seats, number and ease of transfers, comfort, safety and security, etc. Over the years mode choice models have been dealing with the general range of tradeoffs among these factors by the travelers are willing to make a trip (Lerman, 1975; Ben-Akiva and Lerman, 1985; Koppleman and Wen, 2000; Bhat, 2000). Later, (Racca and Ratledge, 2004) added characteristics of a trip as a factor that affects choice of travel mode. Researchers like Stratham and Dueker (1996) and Ye *et al.* (2007) have identified that tour complexity influences mode choice substantially.

The factors discussed above clearly depict that travel time is one of the highly rated factors considered in mode choice and is widely used concept in transportation analysis (Bhat and Sardesai, 2006). Recently, various researchers are considering Value of Travel Time (VOT) as an influencing parameters in choosing the mode. VOT means how much a passenger is willing to pay. Estimating VOT is crucial for cost benefit analysis of transportation projects. Bhat and Koppleman (1999) stated that VOT can serve as an important informal test for evaluating the reasonableness of the model.

2.3. Different Types of Mode Choice Models

There are different types of models available to estimate the mode choice, like aggregate and disaggregate Mode Choice Model. Discrete choice models based on random utility maximization are widely used in transportation applications. They have three different families of models depending upon the functional form of the error term distribution, namely (i) Logit Model; (ii) Probit Model; (iii) General Extreme Value (GEV) Model. Multinomial Logit (MNL) model is the most basic member of the family of GEV models. This model has been used exclusively to model both urban and intercity mode choice until recently. However, the important disadvantage of the multinomial logit model is that it restricts the relative probability of choosing between any pair of unchanged modes due to changes in other modes of travel.

The nested logit model has been used to estimate mode choice models of urban mode-choice and multimodal & multidimensional choices. Hensher *et al.* (2005) recommended adoption of the nested logit model for intercity mode choice estimation. Nested Logit (NL) structure allows estimation of proportions among selected sub-modes, prior to the estimation of proportions between modes. In Dhaka city, with the introduction of new mode of underground MRT, the mode share estimation is estimated through the nested logit model method.

2.4. Nested Logit Model Description and Properties

The nested logit model and multinomial logit models can each be depicted by a tree structure that represents all the alternatives. The multinomial logit model treats all the alternatives equally, whereas the nested logit model includes intermediate branches that group alternatives (Fig. 1.).

The widely adopted paradigm of utility maximization provides a link by which choice probabilities can be estimated given characteristics of the modes and the decision maker. This paradigm holds than an individual acts to maximize his or her utility by choosing among the available alternatives. Utility can then be estimated as a function of the traveler and mode characteristics. The choice probabilities can be computed as functions of the relative utilities among alternatives.

Conventionally, the utility of an alternative, U_{ij} is assumed to be the sum of a deterministic component, V_{ij}, which describes the characteristics of individual i and the attributes of alternative j, and a random term, ε_{ij}, which represents elements not measured or included in the model:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

Where,
U_{ij} is the true utility of mode j for individual i;
V_{ij} is the deterministic or observable portion of the utility;
ε_{ij} is the error or portion of the utility which is unknown.

Further, the measured and included component of the model is represented by a linear additive function that includes parameters, β, and variables, X_{ij}, which are predetermined functions of the characteristics of individual i and the attributes of alternative j:

$$U_{ij} = \beta' X_{ij} + \varepsilon_{ij} \tag{2}$$

Assumptions about the distribution of the error terms ε_{ij} lead to different model structures.

The assumption that the error terms are distributed independently and identically over individuals and alternatives, with a Gumbel (0,1) distribution, yields the multinomial logit model:

$$P_{ij} = \frac{exp(V_{ij})}{\sum_{k \in Ai} \exp(V_{ik})} \tag{3}$$

Where,
P_{ij} is the probability of selecting mode j by an individual i from available modes;
V_{ij} is the systematic part of the utility function of mode j for an individual i;
V_{ik} is the systematic part of the utility function of any mode k from available transportation modes for an individual i;
A is the set of available transportation mode for individual i.

2.5. Estimation of the Nested Logit Model

Estimation of the nested logit model has been most generally undertaken by limited information., maximum likelihood techniques. This method first estimates parameters for the lowest nets(s) and then estimates parameters for successively higher nests based on the computation of the log sum values, which are obtained from the lower nest estimation results.

This sequential estimation leads to a suboptimal log-likelihood at convergence and can yield a lower log-likelihood than the multinomial logit model. Although the parameter estimates are consistent, they are not efficient and have been found to be quite far from full-information estimates in practice.

3. Objective of the Mode Choice Model

Under the Dhaka Mass Rapid Transit Development Project, a new mode of mass rapid transit will be introduced, in Dhaka city with a view to contain the traffic congestion. To find out the mode choice share of this new mode is thereby an important agenda to estimate the demand of the new mode introduction. Therefore, under the study stated preference (SP) survey was conducted to develop the mode choice model. The objective of this survey is to estimate the mode choice probability (modal split) and value of time. The outcome of the survey is used in third step of travel demand modelling.

4. Methodology

4.1. Approach

In order to develop the mode choice model in Dhaka city, the field data collection survey was divided into two stages, namely (i) Pre-Survey; and (ii) Main Survey. Basically, pre-survey was conducted to apprehend the mean value of trip time, cost/fare and to understand the market segmentation of trip and trip maker attributes to design the main survey form in true representation to avoid the biasness towards any parameters towards mode choice.

In pre-survey, the questionnaires were developed taking into account the trip maker attributes which are important factor to mode choice decision and the available modes which the trip maker chose and how much time and cost it takes to complete the trip.

The development of mode choice models on the basis of user preferences collected in the form of Stated Preference (SP) survey data, since in case of Dhaka city, still (as of August 2022) there is none existence of any form of mass transit services like MRT or BRT. SP data has been used to find the utility of modes. However, SP data has been collected asking respondents how they would behave in a hypothetical situation. The structure of Nested Logit Model is shown in the following figure.

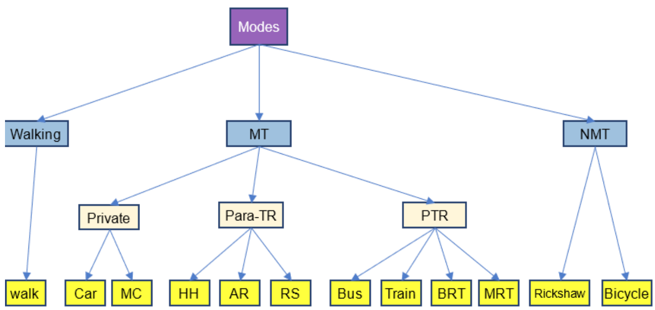

Fig. 1.
Tree Structure of Nested Logit Model

<u>Notations:</u>
MT = Motorized Transport
NMT = Non-Motorized Transport
Para-TR = Para Transit
PTR = Public Transit
MC = Motorcycle
HH = Human Hauler
AR = Auto-Rickshaw/3-Wheeler CNG
RS = Ride Service
BRT = Bus Rapid Transit
MRT = Mass rapid Transit

4.2. Elements of the Choice Making Process

It is observed that an individual (or decision maker) making choice in a wide variety of decision contexts. Generally, it is difficult to have information about the process individuals use to arrive at their observed choice. A proposed framework for the choice process is that an individual first determines the available alternatives; next, evaluates the attributes of each alternative relevant to the choice under consideration; and then, uses a decision rule to select an alternative from among the available alternatives. There are four elements associated with the choice process:

- the respondent/decision maker;
- the alternatives;
- the attributes of alternatives; and
- the decision rule.

In the subsequent sections, it is described briefly about the four elements.

4.2.1. The Trip Respondent/Decision Maker

The decision maker in each choice situation is the individual, group or institution which has the responsibility to make the decision at hand. The decision maker will depend on the specific choice situation. A common characteristic in the study of choice is that different decision makers face different choice situations and can have different tastes (that is, they value attributes differently). For example, in travel mode choice modeling, two individuals with different income levels and different residential locations are likely to have different sets of modes to choose from and may place different importance weights on travel time, travel cost and other attributes. These differences among decision makers should be explicitly considered in choice modeling; consequently, it is important to develop choice models at the level of the decision maker and to include variables which represent differences among the decision makers. First, the respondents were asked about their about socio-economic and personal information, like: gender, age, occupation, car ownership and income.

4.2.2. The Available Alternatives

Individuals make a choice from a set of alternatives available to them. The set of available alternatives may be constrained by the environment. Decision to pick of an alternative by an individual in the context of travel mode choice may be determined by legal regulations (a person cannot drive alone until the age of 16), economic constraints (limousine service is not feasible for some people) or characteristics of the individual (no car available or a handicap that prevents one from driving). The subset of the universal choice set that is feasible for an individual is defined as the feasible choice set for that individual. In this research, it has been considered ten (10) existing modes (as of year 2022) as follows.

Table 1

Number of Modes Considered in SP Survey

SLN	Mode
1	Walking
2	Rickshaw
3	Bicycle
4	Car
5	Motorcycle
6	Tempo/Human Hauler
7	Auto-Rickshaw/3-wheeler
8	Ride Service
9	Bus
10	Train

4.2.3. Trip Attributes

In order to prepare realistic Choice set alternatives, to get representative value from market, the market segmentation has been divided into 3-broad categories in this study: **trip purpose**, **trip length** and **income level**. Then, questions about their real trip in context of trip characteristics was asked to the respondent.

- Trip Purpose;
- Trip Length;
- Average trip length;
- Average trip time.

Trip purpose are then divided into:
- Business trip;
- Commuting trip; and
- Others.

In this study, Trip length are categorized by three types based on the distance. They are Short Trip - the trip considered as the trip length not more than 3.2 km, Medium Trip - the trip considered as the trip length greater than 3.2 km but less than 5.2 km, Long Trip - the trip considered as the trip length greater than 5.2 km.

The travel choice sets based on trip lengths in terms of travel time and length relevant for each respondents current commuting trip so that the travel choices should be given in a context which had some reality for the respondent. Travel choice sets in this study are divided into trip lengths of:

Table 2

Characteristics of Trip Type [considered in SP Survey]

SLN	Trip Length	In Terms of Length (km)
1	Short Trip	1 km ~ 3.16km
2	Medium Trip	3.17km ~ 5.2km
3	Long Trip	More than 5.2km

4.2.4. Mode (Alternative) Related Variables

The attributes of alternatives may be generic or alternative-specific. In the travel mode choice context, in-vehicle-time is usually considered to be specific to all motorized modes because it is relevant to motorized alternatives. Other times, such as wait time at a transit stop or transfer time at a transit transfer point are relevant only to the transit modes, not for the non-transit modes. It is also common to consider the travel times for non-motorized modes (bike and walk) as specific to only these alternatives. In a travel mode choice context, these variables include measures of service (waiting time, in-vehicle time, frequency, reliability of service, etc.) and travel cost. The attributes of the modes used in this survey are:

- Waiting time;
- In vehicle time;
- Total travel time;
- Travel cost;
- Dominant mode of trip.

The choice set considered by an individual depends on decision/trip maker income level. The subset of decision maker income level can be grouped in this study as follows:

Table 3
Income Group [considered in SP survey]

SLN	Income Group	Income Range (in BDT)
1	High Income (HI)	>51,600
2	Medium Income (MI)	20,601 ~ 51,600
3	Low Income (LI)	<= 20,600

4.3. Survey Area

The survey area covered under this research is the Dhaka Metropolitan Area. The transportation network system within this area is supplied by mainly by road and railway. The transportation service is provided by both private and public operators, where majority of service provided by private operators. At present (as of August 2022) there is no mass transit service options in Dhaka city.

4.4. Market Segmentation through Pre-Survey Data Analyses

In order to design the main survey form, it was conducted the pre-survey within the study area to apprehend the market segments. From the pre-survey data outcomes, it was calculated the proportion of trip and trip maker attributes and thereby design main survey form proportions to maintain the homogeneity and true representation of market segment to avoid any biasness. The trip and trip maker attributes proportions are presented in the following sub-sections.

4.4.1. Trip Length

In pre-survey data collection survey 2,789 questionnaire data were collected from the respondent of traveler with different personal and socio-economic attributes. Trip length is one of the attributes of trip where it is categorized by three types in this study as mentioned earlier. In pre-survey study, it is found that Short Trip is 34%, Medium Trip is 26% and Long Trip is 40% among the travelers.

Table 4

Trip Market Segmentation According to Trip Length

SLN	Trip Length Type	Observed Respondent	Trip Length Segment
1	Short Trip	935	34%
2	Medium Trip	732	26%
3	Long Trip	1,122	40%
	Total =	2,789	100%

To design the main survey form, the questionnaire survey forms were made as per the proportion of the pre-survey data collection outcome results.

For practical purpose, to design the main survey form number, it is assumed short trip proportion as 35%, Medium Trip proportion as 25% and Long Trip as 40%.

4.4.2. Trip Purpose

Trip purpose is another attributes of trip. In pre-survey data collection survey out of 2,789 sample data, it is found the trip purpose proportion as per the following table. The main survey form will be designed as per the proportion of the trip purpose found from the pre-survey data analyses.

Table 5

Trip Market Segmentation according to Trip Purpose

SLN	Trip Purpose Type	Observed Respondent	Trip Purpose Segment
1	Business Trip	849	30%
2	Commuting Trip	1,251	45%
3	Other Trip	689	25%
	Total =	2,789	100%

4.4.3. Trip Maker Attributes – Gender

Gender type influence to a great deal in mode choice decision making. In pre-survey data collection analyses, it was found the male/female proportion as shown in the following table.

Table 6

Trip Market Segmentation According to Gender Type

SLN	Gender	Observed Respondent	Gender Segmentation
1	Male	2,373	85%
2	Female	416	15%
	Total =	2,789	100%

4.4.4. Trip Maker Attributes – Income

Income attributes of trip maker has a great influence on mode choice alternatives. Therefore, for true representation of data collection among from the income strata as mentioned in the table below is of utmost important matter. In pre-survey data collection, the respondents proportion belongs to different income stratum is shown below.

Table 7

Trip Market Segmentation According to Income

SLN	Income Type	Observed Respondent	Income Segmentation
1	Low Income	947	34%
2	Medium Income	1,739	62%
3	High Income	103	4%
	Total =	2,789	100%

4.5. Main Stated Preference (SP) Survey Form Design

From pre-survey data analyses, the mean value of each mode attributes have been derived to get the representative value from the market. This calculation is done for every segment as stated in previous section. This mean value then used to design the Stated Preference Survey Form to represent the actual scenario in front of the trip maker. In addition, based on this mean value the **Best** and **Worst** case scenario has been developed for the alternatives depending on trip makers' Income Level (Low Income, Medium Income and High Income) and trip purpose (Business Trip, Commuting and Others).

In order to provide the attributes of MRT/BRT to the users/respondent in the stated preference survey, the information has been taken from the "Preparatory Study on Dhaka Mass Rapid Transit Development Project". For waiting time, in-vehicle time, standing or seating, and cost attributes are taken in consideration of the level of service (LOS) and fare are adopted from the preparatory report as presented in following table. Passengers access to and egress from the station time are estimated considering the standard practice of human walking speed in context of certain level of service, in this case it is considered LOS-E.

Table 8

MRT/BRT Attributes (in case of Dhaka city)

Mode	Items	Year -2025
MRT	Headway (min)	3.5
	Capacity (pax/hr/direction)	33,500
	Commercial Speed (km/hr)	35
	Fare (BDT)	22.6+2.8/km
BRT	Headway (min)	3.0
	Capacity (pax/hr/direction)	2,800
	Commercial Speed (km/hr)	23
	Fare (BDT)	9.9+4.5/km

Source: (JICA, 2018)

4.6. Main Survey – Data Collection

Ideally, in case of Nested Logit Model (NLM), the SP survey data collection should be conducted to complete the full tree of NLM, i.e. from top nest to bottom nest choice alternatives, as shown in the figure below. However, practically it is not possible to conduct interview of a single traveler to complete the questionnaire form of full tree of choice alternatives due to long list of choices in each level of the NL tree. Therefore, in each tree level and in each individual segment different travel choice was grasped. The choice acceptance of available alternatives, in each tree segment is presented in the figure below.

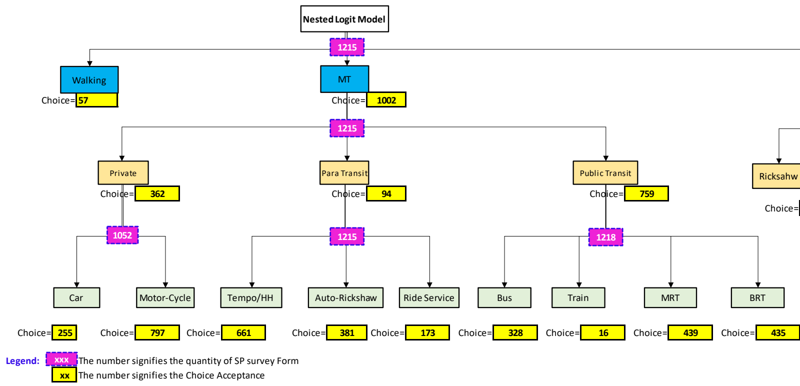

Fig. 2.

Numbers of SP Questionnaire Data Collection under each Tree and Level

Notes: For notations, it is referred to Fig. 1.

The choice adjustment was done by total choices made in full tree of NL as calculated in the table above. After adjustment, the choice acceptance of each alternatives is shown in the table below. The adjustment was done using the following formula.

Adjusted choice sample (any mode) = Total choice questionnaire number (of all modes) divided by any level total choice sample, multiplied by individual mode choice sample number. The adjusted choice acceptance is shown in the table below.

Table 9

Adjusted Choice Acceptance

SLN	Mode	Choice Acceptance	Adjusted Choice Acceptance
1	Walking	57	216
2	Car	255	274
3	Motor Cycle	797	856
4	Tempo/Human Hauler	661	160
5	Auto-Rickshaw/CNG	381	92
6	Ride Service	173	42
7	Bus	328	638
8	Train	16	31
9	MRT	439	853
10	BRT	435	846
11	Rickshaw	595	333
12	Bicycle	459	257
Total		4,596	4,596

5. Data Collection and Analysis

An important issue in the use of stated preference (SP) methods is the quality of the survey and the context in which the survey questionnaire has been developed and the questions are asked. In order to obtained useful results from stated preference methods, the survey needs to be of the highest possible quality and the context in which the stated preference questions are asked should be as realistic as possible. For this reason, in this study it has been conducted pre-survey undertook face-to-face interviews conducted by trained interviewers before going to the main survey.

As the mode choice is developed by nested tree method, therefore data collection was done by nest wise as in the tree. The questionnaire were developed by level and nest wise as shown in the figure below. The framework of the questionnaire was developed by the following level:

First level (dummy) questionnaire:

- Walking;
- Motorized Transport (MT);
- Non-Motorized Transport (NMT).

The questionnaire was developed in different scenario by changing the travel time, fare, income and trip type attributes. The sample form is attached in appendix. Second level (dummy) questionnaire:

- Private;
- Para-Transit (Para-TR);
- Public Transport (PT).

As the same way as mentioned above, the questionnaire was developed in different scenario by changing the travel time, fare, income and trip type attributes. Third Level (alternative level) questionnaire was developed. Private Mode – the alternatives available in the private mode are:

- Car;
- Motorcycle (MC).

The questionnaire was developed by changing the scenarios of respective modes travel time, fare and trip maker income range and by trip type. Para-Transit Mode - the alternatives available in the private mode are:

- Human Hauler (HH);
- Auto-Rickshaw/Three-wheeler CNG (AR);
- Ride Service (RS).

The questionnaire was developed by changing the scenarios of respective modes travel time, fare and trip maker income range and by trip type. Public Transit Mode - the alternatives available in the private mode are:

- Bus;
- Train;
- Bus Rapid Transit (BRT) – Hypothetical Mode;
- Mass Rapid Transit (MRT) – Hypothetical Mode.

The questionnaire was developed by changing the scenarios of respective modes travel time, fare and trip maker income range and by trip type. Non-Motorized Mode - the alternatives available in the private mode are:

- Rickshaw;
- Bicycle.

The questionnaire was developed by changing the scenarios of respective modes travel time, fare and trip maker income range and by trip type.

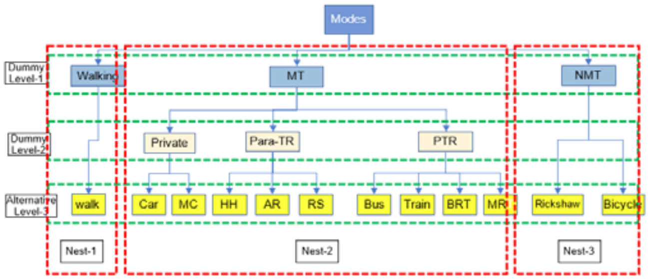

Fig. 3.
Nested Logit Tree Showing the Level and Nest
Note: For notations, it is referred to Fig. 1.

The numbers of questionnaire forms were developed as per the proportions of trip length type, Income range type, Trip Type and gender type as enumerated in the section above.

5.1. Nested Logit Model

Nested logit performs full information maximum likelihood estimation for nested logit models. These model relax the assumption of independently distributed errors and the IIA inherent in conditional and multinomial logit models by clustering similar alternatives into nests. The nested logit model is direct generalization of McFadden's choice model fit by cmclogit. By default, nlogit uses a RUM parameterization. McFadden (1977, 1981) showed how this model can be derived from a rational choice framework.

Choice models are typically derived under the assumption of utility maximizing behavior by the decision maker. Say, the decision makers are enumerated as i = 1, 2, …., N, each facing a choice among a = 1, 2, …., A alternatives. The decision makers derive a certain utility from each possible choice. The utility can be expressed as:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{4}$$

Where,
U_{nj} is the utility of "n" decision maker derives from the alternative j.
V_{nj} is the observed component of the utility, typically modeled as a linear function of observed data vectors.

The term ε_{nj} represents the unobserved component of the utility. The ε_{nj} are assumed to have a random distribution, the precise formulation of which depends on the choice model. This general model is called a random utility model.

Therefore, it cannot certainly conclude that the decision maker will choose a particular alternative from the choice set, rather can probabilistically predict the choice of the decision maker.

For discrete choice model, the probability that decision maker n chooses alternative i can be expressed as:

$$\begin{aligned} P_{ni} &= \text{Prob}(U_{ni} > U_{nj}, \text{ for all } j \neq i) \\ &= \text{Prob}(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \text{ for all } j \neq i) \\ &= \text{Prob}(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \text{ for all } j \neq i) \end{aligned} \tag{5}$$

Where,

P_{ni} is the probability of decision maker n from alternative i

U_{ni} is the utility of decision maker n from the alternative i

U_{nj} is the utility of decision maker n from the alternative j

V_{ni} is the observed utility of decision maker n chooses the alternative i

V_{nj} is the observed utility of decision maker n chooses the alternative j

ε_{ni} is the unobserved component of utility of decision maker n chooses alternative i (is also called the error term)

ε_{nj} is the unobserved component of utility of decision maker n chooses alternative j (is also called the error term)

This probability is the cumulative distribution, namely, the probability that each random term $\varepsilon_{nj} - \varepsilon_{ni}$ is below the observed quantity $V_{ni} - V_{nj}$. The probability that individual n will choose alternative I can be found by integrating above equation.

$$P_{ni} = \int I\,(\varepsilon_{nj} - \varepsilon_{ni} > V_{ni} - V_{nj} \text{ for all } j \neq i)\, f(\varepsilon_i) d\varepsilon_i \quad (6)$$

Where, I (.) is the indicator function equal to 1 when the expression inside the parentheses is true and 0 otherwise and the density function $f(\varepsilon_i)$.

The mode choice modeled developed in Dhaka city with having twelve (12) alternatives including two new mode of MRT and BRT along with the existing ten (10) available modes as mentioned earlier of this section.

The data collection of SP survey questionaries are analyses using the software Stata 16.

5.2. Alternative Specific Variables and Case Specific Variables

Some observed measures are characteristics related to the alternative. For example, if alternatives are different modes of public transportation – Bus, MRT, BRT or Train – one measure might be the cost of ticket for each alternative. We call these measure ***alternative specific***.

Other observed measures are characteristics of the decision maker alone, for example, his or her income or age, We call these measures ***case specific***. Because case-specific measures may affect different alternatives in different ways, there is a not a single coefficient estimated for each case-specific differences among alternatives due to the case-specific variable.

5.3. Data Analyses in Stata

To analyze the data, it is used the Stata-16 software platform. Before going into Stata software, it is needed to prepare the data to fit in the nested logit model command. One important matter of concern in case of nested logit regression is that although the tree in nested logit analysis are often interpreted as implying that the highest level decisions are made first, followed by decisions at lower levels, and finally the decision among the alternatives at the bottom level, no such temporal ordering is implied. In this case, it is not assuming that the trip maker first choose Motorized and Non-Motorized Mode then choose Private, Para-Transit, Public Transit and then choose the particular mode; it is rather simply the trip maker choose any one of the twelfth (12) available alternative modes.

From the survey data collection, there are 4569 trip makers and their choice of twelve (12) alternative modes. Car and Motorcycle from Private mode; Human-Hauler, Auto-Rickshaw, and app based Ride Service from Para-Transit Mode; Bus, Train, BRT, MRT from Public Transit Mode; Cycle and Rickshaw from Non-Motorized Mode; walk from Pedestrian mode. It is intendent to model the decision of which alternatives will be choose by the trip maker as a function of mode attributes (IVTT and Cost/Fare), Trip maker attributes (Income and Gender), the trip attributes (trip length [short, medium, long], trip type [business, commuting, others]).

Because each trip maker chose among the twelve alternatives, there are 12 observations in the dataset for each trip maker. The variable chosen is coded 0/1, with "1" indicating the chosen scenario and "0" otherwise.

Level, or decision level, is the level or stage at which a decision is made. The tree above has three levels. In the first level, type of mode is chosen – walk, motorized, non-motorized. The second level type of motorized transport mode is chosen – private, para-transit, public transit and in the third level the specific mode is chosen among the 12 alternatives.

Bottom level is the level where the final decision is made.

Alternative set is the set of all possible alternatives at any given decision level.

Bottom alternative set is the set of all possible alternative at the bottom level. In this model the bottom alternatives set is all twelve of the specific modes.

Alternative is a specific alternative within an alternative set. In the first level of this model, "Motorized Transport" is an alternative. In the second level, "Public Transit" is an alternative. In the third level, "MRT" is an alternative.

5.3.1. Data Setup and the Tree Structure

Identifying the first-level set of alternatives
To fit a nested logit model, it is needed must to create first a variable that defines the structure of the nested logit tree. To run nlogit, it is needed to generate a categorical variable that identifies the first-level set of alternatives are Walk, Motorized Transport and Non-Motorized Transport mode. The sequential steps/command in Stata software application are presented below:

Statistics > Choice models > Nested logit model > Setup for nested logit model

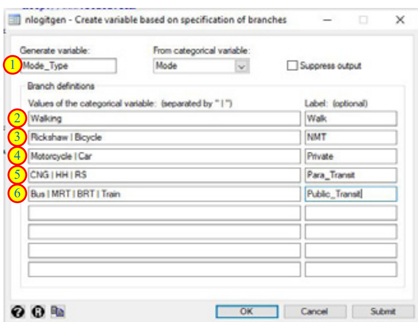

Fig. 4.
Sequential Command and Variables Setting in Stata Nested Logit Function

5.3.2. Estimation of Mode Choice Probability

With the type variable created that defines the three types of modes, now it can be examined how the alternative-specific attributes (time, cost, distance) apply to the bottom alternative set (the twelve modes) and how trip maker attributes (income, gender) and trip attributes apply to the alternative set at the first decision level (the three types of transport mode).

Statistics > Choice models > Nested logit model > Display nested logit tree structure

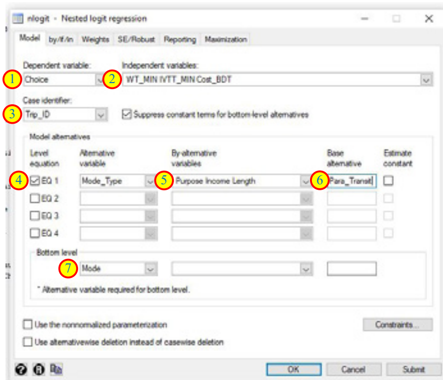

Fig. 5.
Nested Logit Regression Stata-Interface Menu

First, the equation specifies the dependent variable, choice, and three alternative-specific variables, IVTT, Cost/fare, seat/standing. It is referred to these variables as alternative specific because they vary among the bottom-level alternatives, the mode.

For the second equation, it is specify the type variable. It identifies the first-level alternatives, the modes types. It is specified two case specific variables, income and gender. Here it is obtained a parameter estimate for each variable for each variable for each alternative at this level. That is why it is called these variable lists "by-alternative" variables. Because income and gender do not vary within each case, to identify the model, one must specify the alternatives set of parameters as zero. It is specified the base (Train) option with this equation to restrict the parameters for the family alternative.

Third, select the case Identifier variable that identifies the cases. For choice model, the case is a single statistical observation but consists of multiple Stata observation. Each distinct value of case id represents a single statistical observation, that is, a case.

Fourth, under the model alternatives, setting the Alternative variable as Mode Type that was developed in the model set up (as mentioned above).

Fifth, under the By alternative variables, select the variables of the trip maker as Trip Purpose, Income and Trip Length.

Sixth, under the Base Alternative, select the base alternative as Para Transit mode.

Seventh, at the Bottom Level, select the Mode as mode type.

5.4. Results – Nested Logit Mode Choice

Each mode's choice, considered under this study, or modal split is expressed in terms of percent probability. Mode choice results (for the year 2028) are represented in the following table with chart.

Mode	Mode Choice Probability
Walking	5%
Bicycle	2%
Rickshaw	11%
Car	3%
Motorcycle	9%
Auto-Rickshaw/CNG	3%
Human Hauler (HH)	3%
Ride Service	5%
BRT	4%
Bus	40%
MRT	12%
Train	3%

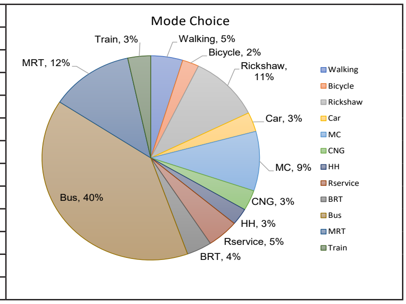

Fig. 6.
Mode Choice Probability Outcome Results

6. Value of Time (VOT)

6.1. Introduction

Travel time is an important attribute of any transportation system. It is a significant factor that shapes the decisions of travelers in the transportation market. Travel time savings are found to be the greatest benefit of transport study such as highway and public transport improvements and one of the major intangibles in transport cost-benefit analysis. Value of travel time plays a key role in traveler's mode choice behaviour and varies significantly with varying socio-economic conditions.

Value of travel time can be defined as the price people are willing to pay to acquire an additional unit of time, while the value of travel time saving (VTS) can be defined as the willingness to pay for time reallocation between two alternative activities. When evaluating consumer's choice among different transportation alternatives, the value of time is a fundamental concept. The value of time is calculated as a trade-off ratio between the time coefficient and the cost coefficient. VOT depends on several parameters and varies from country to country, industry to industry, and even from individual to individual.

Travel time savings are the main benefit outturn from investments in transport infrastructure and service development. Transport investment appraisals quantify travel time saving benefits using standard unit values provided by an appropriate transport/highway agency. In this study, the value of time is estimated for different income groups as well as different trip lengths. The data analyses is limited to estimate the value of travel time in the context of trips of its kind of Business, Commuting and Others (recreation, social, etc. trips) trip types in Dhaka city.

6.2. Literature Review

Several research works have been done on both the theory and practice of valuing the travel time. The widely accepted theory of time allocation and how time is saved is often referenced to Becker (1965). Different researchers employed different approaches for estimating the value of time. Beesley (1965) and Cesario (1976) estimated the value of time saved in commuting to work as a function of wage rate.

The national value of time studies conducted in many countries (UK, Sweden, Finland, France, etc.) considered the experimental data collection methods such as stated preference, along with results based on conventional revealed preference method. Wardman (1987) conducted an empirical study using stated preference data to determine the distribution of individual values of time. Ahsan *et al.* (2002), Richardson (2006), Antoniou *et al.* (2007), Teseng and Verhoef (2008) and Xumei *et al.* (2011) also employed stated preference approach for estimating VOT.

For estimating VOT researchers employed multinomial logit model (MNL) and mixed logit model to estimate the value of time. Ordered logit model is chosen in this study to estimate VOT for different income groups and different trip purpose.

6.3. Theoretical Framework

Value of time can be defined as the maximum amount of money that people are willing to sacrifice to save one unit of time, provided that all other trip related attributes remain constant. In simple linear models, the VOT is calculated as the ratio of parameter estimates related to travel time and travel cost, holding all else constant. In calculating VOT, it is important that both attributes (i.e. travel time, and travel cost) to be used in the calculation are found to be statically significant, otherwise no meaningful VOT can be calculated.

Stated Preference (SP) data with the decision maker facing two alternatives in each choice situation was used. The alternatives differ on following attributes:

- Travel time TT [in minutes];
- Travel cost TC [in BDT] [where, BDT stands for Bangladesh currency in Taka].

The utility function of the alternative has the form:

$U_i = \beta_{tt}$ x TT + β_{tc} x TC +$\mathcal{E}$;
[where, TT = Travel Time
and TC = Travel Cost] (7)

Where β_{tt} and β_{tc} represent respective parameter that are going to be estimated from data.

Parameters β_{tt} and β_{tc} were estimated likelihood method using statistical analysis software. The value of travel time was obtained by the substation of estimated values of β_{tt} and β_{tc} in the formula.

VOT = $\frac{\beta tt}{\beta tc}$ x 60 BDT/hr.
[where, VOT = Value of Time] (8)

6.4. Analyses Outcome

Ordered logit model is formulated using the nested logit model data pool collected for mode choice analyses. Ordered logit model are used to estimate the relationship between the ordinal dependent variable "choice" based on the set of independent variables of waiting time, in-vehicle time, and cost variables that are categorical or ordered like mean, best, better, worse and worst scenarios developed when designing the questionnaire forms.

From ordered logit models, it is estimated the value of time. The coefficients of the variables of "Waiting Time (WT)", "In Vehicle Travel Time (IVTT)", and "Cost BDT" has been taken from the Stata run outcomes (as attached in Appendix-3). Then the ratio of time to the cost is the value of time (VOT), or in other words the value of time in exchange of cost has been estimated. In the table below, some values are quite suspicious, like cost co-efficient of Low Income, of which the coefficient of cost should be negative, or in other words it can interpreted as the trips made by low income groups for trip purposes (like social, recreational, festival, etc.) trip makers are less concern about the cost.

The value of time of high income group is lower than other two groups, which does not reflect the real world scenario, however, data analyses results outcome is like this.

Table 10
Value of Time (VOT) as Per Trip Segment

Trip Segment	Coefficient (Waiting Time in Minutes)	Coefficient (In Vehicle Time in Minutes)	Coefficient (Cost BDT)	Value of Time (BDT/Min)		Ratio (Waiting/ In Vehicle Time)
				With Respect to Waiting Time	With Respect to In Vehicle Time	
High Income Business Trip	-0.076	-0.014	-0.0147	5.166	0.979	5.275
High Income Commuting Trip	-0.127	-0.018	-0.028	4.594	0.637	7.210
High Income Other Trip	-0.110	-0.017	-0.033	3.373	0.504	6.689
Middle Income Business Trip	-0.097	-0.015	-0.006	16.849	2.547	6.616
Middle Income Commuting Trip	-0.100	-0.014	-0.010	10.417	1.423	7.319
Middle Income Other Trip	-0.109	-0.015	-0.007	16.452	2.243	7.335
Low Income Business Trip	-0.090	-0.016	-0.011	8.102	1.477	5.486
Low Income Commuting Trip	-0.105	-0.023	-0.011	9.825	2.158	4.554
Low Income Other Trip	-0.090	-0.024	-0.017	5.295	1.390	3.808

The results indicate that the middle income group have higher value for travel time saving compared to the high income group (which is non-intuitive). However, this is actually plausible since the high income group are indifferent of time pressing issue (because they possess the power to defer the schedule time) and may have better access to information, be more receptive to technology and more inclined to opt for new modes. On the other hand, the middle and low income group are better concern about time pressing issue (in case of hurry to attend a meeting, or other events) this may be due to justification bias as well (a common problem of SP is people often opt for what they should do rather than what they would really do in SP, the problem being higher for high educated segments). In any case, because of the low statistical significance, the income segmented results should not be given much weightage.

Apart from that there was limitation in data collection survey. In case of nested logit model questionnaire survey, the questionnaire survey form is quite long, which might include error in data collection. Another weakness is that the survey was conducted in bus stops, bus terminal, etc., where high income group people are less likely to available to interview.

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