HETEROGENEITIES IN DEMAND CURVE FOR MRT SERVICES IN DHAKA CITY, BANGLADESH

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The high socio-economic disparity, especially in developing countries make people value public transport service attributes such as crowding differently. Such heterogeneities in demand are often ignored while planning for new public transport systems. This study aims to analyze this sensitivity in the effect of crowding on mode choice disutility based on the income of travelers. A stated preference survey regarding crowding in a new mass rapid transit (MRT) system was conducted in the city of Dhaka, Bangladesh. Mixed logit models were employed to analyze data collected from 370 people, making a total of 2,139 trips, divided into three groups based on their income. The results showed that the high-income group valued crowding nearly three times higher as compared to the low-income group in the case of high crowding. The findings of the logit models were then utilized to perform a sensitivity analysis on the log-sum measure of consumer surplus as a function of fare and crowding levels.

Key Words: Overcrowding*, MRT, Heterogeneities in travel demand, crowding cost, Consumer surplus*

1. INTRODUCTION

Planning of new public transport systems such as mass rapid transit (MRT) often ignore the heterogeneities in demand that might arise due to the existing socio-economic disparities. The world is becoming increasingly disparate and the decisions made by people will be influenced by these differences. Such disparities exist both in the developed and the developing world but are more prominent in developing economies. Public transport systems in developing economies are marred by issues related to service quality, safety, security and crowding among others, and the value people attach to these factors depend on their social standing. For example, during crowded situations inside public transport systems, people with relatively higher income will value their travel time savings differently as compared to people with lower income. It is possible that people with relatively higher income might be willing to pay more to reduce their travel time during crowded situations. In addition, this heterogeneity might also reflect in their decisions, as people with relatively higher income might prefer private modes such as cars over traveling in a congested public transport system.

Accounting such heterogeneities have been often neglected but is necessary to make appropriate policy decisions. Crowding in public transport refer to the congestion either inside vehicles or at the vehicle stations (or at platforms). It primarily has two dimensions, objective and subjective[1)]. The former refers to the actual physical conditions inside the transport vehicle and there exist different methods to measure the crowding condition. Standing passengers per square meter, passengers in excess of capacity, load factor, and proportion of seat occupied (with standing passengers per square meter) are few of the commonly used objective measures of crowding [1,2)]. The second dimension of crowding is the subjective perception of it, as different people attach different value to crowding and how it impacts them. These perceptions might depend upon the actual objective level of crowding, personal and socio-economic characteristics of the traveler, and their previous experiences. Traditionally, discrete choice models have mostly accounted for the effects of travel time and travel cost on the mode choice. However, the consideration of crowding conditions in these models is gaining popularity. Many studies in the recent past have incorporated crowding within the utility equations. The most common way is to introduce a crowding variable as an interaction term with travel time, indicating a higher disutility for longer trips[2–4]. This has been mostly done in studies where the impact of crowding on value of travel time savings (VTTS) was estimated using crowding-related time multipliers. In other studies, a crowding variable was directly introduced to evaluate its relationship with mode choice[5]. In addition, apart from mode choice models, crowding has been used as a variable to test its effect on public transport route choice, public transport fare optimization, waiting time, travel time reliability, and wellbeing of travelers[2]. However, an area of research which has not received enough attention is the analysis of the heterogeneities in the effects of crowding due to socio-economic disparities. Especially, in developing economies; where these heterogeneities will be more prevalent. In addition, while analyzing these heterogeneities, it will be interesting to evaluate how the contribution of crowding (as compared to other variables) towards the total (dis)utility varies based on socio-economic groups. A focus on this aspect would be necessary to make certain policy decisions such as variable fare price on public transport systems based on comfort.

The aim of this paper is two-fold. First, we analyze the sensitivity in the effect of crowding on mode choice disutility based on the income of travelers. Second, we perform a sensitivity analysis on the log-sum measure of consumer surplus as a function of fare and crowding levels for testing price setting scenarios. We employ mixed logit models to achieve the above-mentioned objectives by using data from Dhaka, Bangladesh. A stated preference survey was conducted for a new MRT system, where travelers were asked to choose based on varying levels of relevant travel attributes. A special focus was provided to understand their sensitivity to crowding levels along with collecting information on other commonly used travel attributes such as travel time, travel cost, and service frequency. Dhaka's metro system is scheduled to begin services in late 2020 and we believe that our work of analyzing the heterogeneities in sensitivity to crowding variables and their magnitude of influence on the total utility will provide pertinent insights for researchers and policy makers.

The rest of the article is organized as follows. Section 2 provides a review of the literature on the treatment of crowding variables in mode choice models and the evidence from developing countries. Section 3 describes the study area, survey methodology, and the data to be used for the mixed logit models. Section 4 describes the methodology adopted in this study. Section 5 discusses the results. Finally, in section 6 we conclude the paper with discussions on the policy implications of our findings and the way forward for the research.

2. LITERATURE REVIEW

(1) Crowding in mode choice models

The treatment of crowding related variables has varied in mode choice models across literature. There are two distinct aspects of how crowding variables were utilized in the mode choice utility equations, a) what kind of variable i.e. which crowding indicator was used b) how it was used e.g. if it was used as a continuous or a dummy variable and whether it was added in the utility equations in interaction with some other service level attribute. This brief review of the literature covers both the aspects, while identifying gaps in the literature. Tirachini et al. [2] estimated five separate mode choice models (one each for MNL and random parameters model) with different treatment of crowding related variables in the utility equations. They compared the model with 1) no crowding variable with models which included 2) density of standees (in pax/m^2), 3) density of standees and the proportion of seat occupied, assuming that crowding will affect passenger disutility only when at least 25% of the seats are occupied, 4) load factor above 60%, assuming that crowding will affect passenger disutility only when the load factor is above 60%, and 5) load factor above 90%, assuming that crowding will affect passenger disutility only when the load factor is above 90%. All crowding variables mentioned above where introduced in the utility equation as interaction terms with travel time, indicating that crowding will cause a higher disutility if the travel time is longer. Similarly, in Yap et al.[6] two crowding variables were introduced in the utility equations of MNL and mixed logit models as an interaction term with travel time. First variable was seat occupancy, which represented the ratio between expected passenger load and the vehicle seat capacity. The seat occupancy for each alternative and time period was calculated based on the weighted average of seat occupancy and travel time. In similar fashion, the second variable, density (in pax/m2) for each link and time period was also calculated by taking the weighted average (see Yap et al. [6] for formulations). In addition, they segmented the models based on whether the passengers were frequent travelers or not.

Other studies used a combination of the above-mentioned crowding variables as well. Dummy variables representing only the crowding level i.e. not as an interaction term was used in Shen and Chatman[7]. Meanwhile, in both, Björklund and Swärdh[8] and Whelan and Crockett[9], dummy variables representing crowding levels (both during being seated and standing) in interaction with travel time were used. Continuous variable for density and dummy variable representing whether the passenger was standing or not was used in the utility equations by Tirachini et al.[4] and continuous variables representing number of standing passengers and proportion of passengers seated was used in Hensher et al.[10]. In addition, dummy variables representing passenger density with latent variables representing attitudes towards crowding in hybrid discrete choice models was used in Márquez et al.[11],whereas, Sahu et al.[5] used a combination of a continuous variable for crowded seat time, dummy variables for standing up to 10 min and standing from 10-20 min (at a density of 7-9 pax/m2), and a continuous variable representing standing time in super dense crush load (13-15 pax/m2) in the utility equations. Batarce et al.[12] structured the crowding density as a function of individual characteristics, whereas, Ho and Hensher[13] jointly estimated mode and time of the day choice by including a continuous variable for crowding representing the number of passengers standing. The literatures on the use of crowding as an independent variable show that there is no one standard measure. The variables have been used in ways to represent both linear and non-linear relationships with the (dis)utility. However, it is obvious that the disutility derived from higher levels of crowding will be much higher as compared to a relatively lower level. In addition, the assumptions on the crowding variable and the way it is included in the utility equations might affect the final estimation results.

(2) Evidence from Developing countries

Even though crowding in public transportation is a universal phenomenon, the conditions in developing countries, especially in cities with high population density are extreme. Pucher et al.[14] described the crowding in Mumbai, India's local trains as super dense crush load representing a standing density more than 12 pax/m^2. The income disparities in these countries make many passengers captive riders of public transportation, leaving them without any choice but to travel in uncomfortable conditions. The studies on crowding from developing countries show how researchers have dealt with the variable so far. Katz and Rahman[15] presented evidence on the levels of crowding in the buses of Dhaka, Bangladesh. They noted that local buses in the city observed higher levels of crowding as compared to ticketed buses.

Basu and Hunt[16] observed that train choice behavior in Mumbai, India is affected by headway time and train ride time associated with crowding level. In addition, they noted that an increased level of crowding resulted in a higher VTTS. In addition, they also segmented mixed logit choice models based on income and observed that people with relatively lesser monthly income were willing to pay more for reducing their travel time; a counterintuitive finding given the expectation is that richer people would value their time savings higher in comparison. Sahu et al.[5] estimated segmented MNL models based on gender, age, occupation type, income, and trip length for the passengers of Mumbai, India. They observed that female passengers were more sensitive to crowding (for all crowding variables) as compared to male passengers. Meanwhile, people with a relatively higher income were more sensitive to the crowding variable which denoted the standing time during super dense crush load.

In another similar study investigating the effect of crowding on willingness to pay (WTP) from China, Gao et al.[17] observed that socioeconomic individual variables such as age, gender, income, and education levels influence the WTP for reducing crowding. The studies from developing countries establish the relevance of socioeconomic variables while estimating the impact of crowding on mode utility. However, there exists a gap in the understanding of the relative importance of predictor variables. It seems like, so far either the effect of crowding with or without interaction with other variables has been predicted but people might make decisions based on all service attributes of available modes and other individual level socioeconomic characteristics. In addition, further segmenting the analysis based on certain socioeconomic variable such as income would further deepen our understanding on how people belonging to different income groups value crowding in comparison to other travel related and socioeconomic variables.

3. STUDY AREA, SURVEY AND DATA

(1) The Study Area

Dhaka is the capital city of Bangladesh. According to World Bank, it is one of the fastest growing mega cities (growth rate 3.61%) of the world with a population of 20.3 million and expected to exceed 31.0 million by 2035. The overall transportation system of Dhaka city is very poor and unplanned. In the report of Copenhagen consensus center, Gallagher[18] has marked Dhaka's transport as one of the worst transport systems. In 2015, the Government of Bangladesh commissioned a Revised Strategic Transport Plan (RSTP), which proposed constructing five metro rail lines, two rapid bus routes, and 1,200 kilometers of new roadways.

The present public transport network in Dhaka includes mostly Bus, Taxi, Three-wheeler (run by CNG) and Laguna (small capacity bus, around 10 passengers per coach). However, bus is the leading mode compared to other modes in terms of passenger carrying. The bus service in Dhaka is much unplanned and traffic regulation is very poor. As a result, there is a traffic gridlock in the roads of Dhaka.

Considering the overall traffic condition, MRT line-6 has been recommended as priority set by the JICA consultants. As per recommendation, the construction of MRT line 6 has been started in 2016 and expected to start operation by 2021. MRT line 6 has been chosen for the present study.

The study area has been shown in Fig 1. The pink dots represent the residential locations of the respondents of the SP survey that has been conducted for this study. The blue dots represent the workplace location of the respondents. These office and residential location data were recorded during the survey.

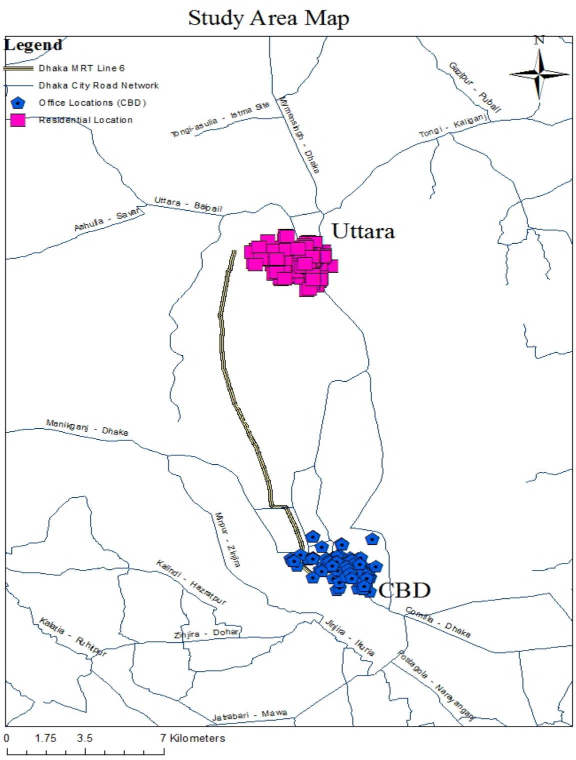

Fig 1 The Study Area

(2) Survey and data

A commuter survey was conducted to collect data in December 2019. As Metro Rail Transit (MRT) line-6 of Dhaka city is scheduled to start operation in 2021 in Uttara-Motijheel route, so we conducted a combined survey for the commuters of Uttara-Motijheel route. We represented different attributes of metro services in stated preference choices. Also, the present travel mode information data were collected in revealed preference part. We conducted face to face interview of the prospective metro commuters. Respondents were interviewed both in office and household. Total 416 samples were collected. After correction 370 responses were found to be correct. To know the different attributes of existing travel behavior, we provided a list of existing travel mode and asked the respondents about which of the following modes are available to them. The respondents checked the modes which are available to them and provided relevant values of the attributes for available modes. In addition, we asked the respondents about their regular commuting mode. Survey respondents were also asked whether they do any kind of multi-tasking or not. If their response is yes, they had to give the list of multi-tasking activities they do during their commuting. This is perhaps one of the indirect ways to measure the value of time of the respondents. This is because if multi-tasking activities are hampered, they will value the crowding in a different manner. They will also value the crowding in the SP questionnaire in a way as different dimensions of crowding will affect their multi-tasking activities. However, there are other type of impacts of crowding has been discussed in introduction part. In the SP choices alternatives were described by travel time, fare, frequency and crowding levels. In the SP questionnaire we asked the responded by showing the attributes of MRT services to choose between MRT and present travel mode. In MRT attributes, crowding dimension have been shown both graphically and with written description. At the beginning, every respondent was briefed about the meaning of all terms and explanations about the survey questionnaire so that they can answer properly.

(3) Crowding dimension

In literatures, crowding dimensions have been defined in many ways. In our present study crowding has been shown in six different levels. Each crowding level is described in terms of occupancy level compared to the normal capacity of the coach, density of standing passengers, physical proximity between passengers and easiness of multi-tasking activities. We also have shown the crowding levels graphically. Table 1 provides the description of crowding levels used in the survey. Crowding dimensions were also shown graphically in the survey questionnaire as shown in Fig 2.

Table 1 Crowding level-wise distribution of passenger density and occupancy level

Crowding Level	Density of standing Passenger (Passenger/m^2)	Occupancy level (to normal capacity)
1	0	20%
2	3	100%
3	6	150%
4	8	200%
5	10	250%
6	12	300%

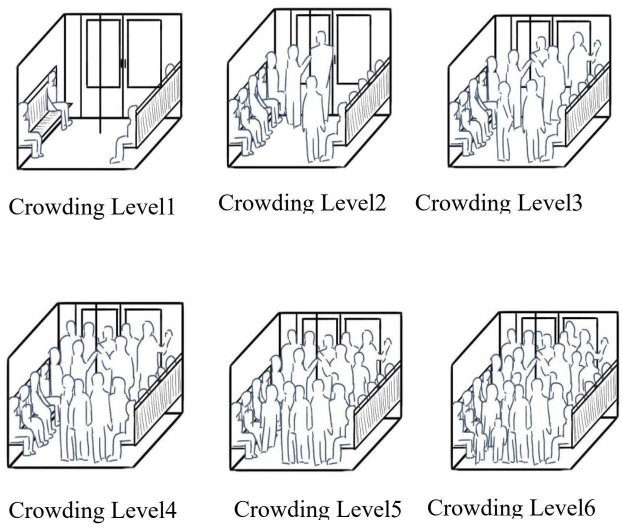

Fig 2 Graphical representation of crowding dimensions

In SP questionnaire we represented the travel time, frequency and fare of MRT services in 3 levels. We designed SP questionnaire by orthogonal design using R. Levels of variables used in SP questionnaire are shown in the Table 2.

Table 2 Levels of MRT variables used in SP questionnaire

Variables	Levels
Travel Time (minute)	30, 40 & 50
Fare (BDT)	70, 150 & 300
Frequency of Services (minute)	4, 7 & 10
Crowding Level (as mentioned)	1, 2, 3, 4, 5 & 6

(4) Descriptive Statistics of the survey data

In terms of gender we only have 14% female respondents compared to 86% male respondents. Whereas proportion of female population is about 50% in Bangladesh, even women employment rate in Dhaka city is higher than 14% compared to man. We observed huge heterogeneity in socio-economic factors. There are 24% respondents whose monthly income is less than 50 thousand BDT, 40% of the respondents have income between 50 thousand to 100 thousand and remaining 36% respondents have income more than 100 thousand BDT per month. We also observed heterogeneity in age distribution of the respondents. Almost half (47%) of the respondents have age between 31 and 45, 20% respondents have age below 30 years. Remaining population (33%) has age above 46 years to 65 years. In educational qualification, majority (62%) of the respondents have a master's degree or higher qualification. Remaining population has highest degree of bachelor (19%), higher secondary (11%), secondary (7%), diploma and primary education. Almost half (54%) of the respondents have private job as profession. Remaining population's professions are divided in government job, business and student. Bus has been found as the major (75%) mode for regular commuting. Other regular commuting modes are private car (16%) and motor bike (9%). Travel time for the commuters from home to workplace is found very long; this is obviously because of congestion on the road and existence of motorized and non-motorized vehicle in the same carriageway of the road. Also, taxi and other ride sharing services often require extra pay because of longer travel time which is not affordable to low income people. However, longer travel time induces increased generalized cost for the commuters. Crowding dimension in bus and MRT is not same. So, to get the idea about crowding intensity that a commuter faces in the bus we asked them to mention the crowding level they face in bus is near to which crowding level described to represent the crowding level of MRT services. 4% respondents said they face the crowding near crowding level 6 of MRT services, 13% said they face like level 5 crowding of MRT services, 24%, 28% and 29% said their experience is like level 4, level 3 and level 2 of those for MRT services respectively. Only 2% said their experience is like level 1 crowding in MRT services. Overall distribution of service variables for different modes is shown in Table 3.

Table 3 Distribution of variables in the existing/present travel mode

Mode	Travel Time (min)			Fare (BDT)			Average Waiting time (min)
	Min.	Max.	**Avg.	Min.	Max.	Avg.	
Bus	45	180	115.5	50	200	84	5.6
Private car	40	165	106	200	1050	362	
Taxi/Uber	35	165	101	200	830	441.20	
*CNG	40	165	101	170	550	356	
Private Motorbike	35	125	85	50	200	92.5	
Shared Motorbike	31.5	130	83	150	350	209.5	

*CNG = 3-Wheeler run by compressed natural gas (CNG), **Avg. = Population average

4. METHODOLOGY

Methodology contains two parts. First, estimating crowding sensitivity and secondly, price setting scenario analysis. Error component mixed logit model has been used for estimating crowding sensitivity and stochastic user equilibrium approach has been used for estimating equilibrium flow for scenario analysis. The methodology is discussed separately in the following section. To estimate the impact of crowding on different income groups, the whole sample has been divided into three income groups; income less than or equal to 50,000 BDT has been defined as low-income group (LIG), income above or equal to 120,000 BDT has been defined as high income group (HIG), remaining sample has been defined as middle income group (MIG).

(1) Modelling approach to estimate heterogeneities of crowding sensitivity

In this study, an error component mixed logit model has been used for the analysis of the data. This type of model can be used without a random-coefficients interpretation, as simply representing error components that create correlations among the utilities for different alternatives. Error-component and random-coefficient specifications are formally equivalent. Under the random-coefficient motivation, utility is specified as[19)]

$$U_{nj} = \beta_n x_{nj} + \varepsilon_{nj} \tag{1}$$

With random parameter β_n, the coefficients β_n can be decomposed into their mean α and deviations μ_n, so that

$$U_{nj} = \alpha x_{nj} + \mu_n x_{nj} + \varepsilon_{nj} \tag{2}$$

The terms $\mu_n x_{nj}$ along with ε_{nj}, define the stochastic portion of utility. That is, the unobserved (random) portion of utility is $\eta_{nj} = \mu z_{nj} + \varepsilon_{nj}$, equation 2 can be re written as

$$U_{nj} = \alpha x_{nj} + \eta_{nj} \tag{3}$$

The portion denoted by η_{nj} represents the error component for error component model.

As our ultimate objective is to estimate the impact of fare on consumer surplus by taking crowding effect in consideration, first, we will estimate the individual impact of every crowding density we defined in our original survey. So, in first approach we will estimate the disutility coming from crowding by taking the dummies of every crowding level. Later we will investigate the continuous impact of crowding using a BPR type of non-linear function. In the following sections both the approaches are discussed separately.

(2) Method to estimate the effect of crowding levels as dummy variables

To estimate the impact of crowding disutility for every level of crowding, we used dummies for every crowding level in our modeling equation. We defined every level as "1" if the user faces the particular crowding level otherwise "0". As we have six crowding levels, we incorporated five crowding levels in our utility equation taking crowding level 1 as reference level. We used error components mixed logit model to estimate the impact of crowding. The functional form of the utility is as follows:

$$U_{ij} = asc_j + \beta_{tt} * TT_j + \beta_{hw} * HW_j + \beta_{tc} * TC_j + \sum_{cl=2}^{6} \beta_{cl} * CL_{jcl} * TT_j + ec_i \tag{4}$$

Where,

U_{ij}= Utility of an individual for choosing an alternative

asc_j= Constant specific to the alternatives

β= Parameter associated with variables

TT_j= Travel time for alternative

HW_j= Headways for an alternative

TC_j=Travel cost for an alternative

ec_i= Error component

Travel time has been taken as interaction term with the crowding level as it is suggested by many studies.

(3) Method to estimate the continuous impact of crowding

In this study, a BPR type function has been adopted from Tian et al [20)], to estimate the value of in-vehicle crowding. The functional form of our utility equation incorporating non-linear crowding effect is as follows:

$$U_{nj} = asc_j + \beta_{tt} * TT_j + \beta_{hw} * HW_j + \beta_{tc} * TC_j + \gamma\left(\frac{v}{K}\right)^{\rho} * TT + +ec_i \tag{5}$$

Here,

v = actual passenger in the coach

K = normal capacity of the coach

γ= represents scale parameter associated crowding disutility ρ = scale parameter associated crowding disutility

Meaning of other symbols has been mentioned in earlier paragraph. If the value of v (i.e. number of passenger) is smaller than K (actual capacity), the train will remain in normal crowding condition though there will remain some standing passenger as the normal transit capacity allows some standing passenger. However, when v becomes greater than K, their ratio becomes more than 1 and increases the overall crowding disutility. So, $\frac{v}{K}$ ratio has significant impact on the crowding cost. As γ and ρ are location specific parameters. We will estimate the value of γ and ρ from this model. For better estimation, we used grid search approach to estimate the ρ parameter. For a range of values of ρ, γ has been estimated. However, the values of ρ and γ that have given the maximum final loglikelihood have been considered as the best values of ρ and γ. However, in this study we used this BPR type function to consider the in-vehicle transit crowding of developing city like Dhaka.

(4) Fare scenario analysis

In this research, scenario analysis has been done for fare setting. Different scenarios have been created by varying the metro fare. For every scenario, equilibrium flow in metro has been estimated. Then, impact of fare has been analyzed for income group-wise passenger demand distribution. Also, the impact of fare on income group-wise consumer surplus has been estimated for every scenario. The steps involved in the scenario analysis are shown in Fig 3.

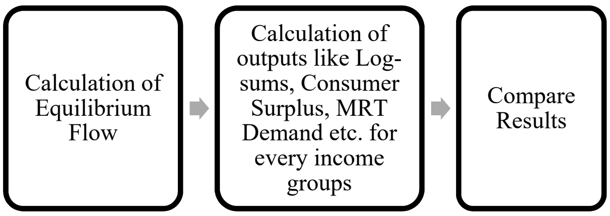

Fig 3 Steps of pricing scenario analysis

(5) Method to estimate equilibrium flow

There are several assumptions for calculating the equilibrium metro flow for the income groups, which includes

Road congestion has been ignored, i.e. road will have sufficient capacity to take care any number of traffic and no disutility will be induced from the congestion

Bus crowding has been kept fixed at occupancy level 150% for every scenario

Stochastic User Equilibrium (SUE) approach has been used to calculate equilibrium flow

Capacity of metro will remain fixed throughout the scenario

For equilibrium flow calculation of metro, method of successive averages (MSA) is used.

There are several secondary data which are required to calculate the equilibrium flow have been taken from different reports. The general information is shown in Table 4.

Table 4 General information for equilibrium metro flow calculation

Item Name	Item Description
Peak hour passenger (number)	3,34,081 (JICA Study Report, 2015)
Distribution of passenger based on income-groups (number)	Low-income group (LIG) (44.10%) = 147330 Middle-income group (MIG) (35.50%) = 118599 High-income group (HIG) (20.40%) = 68153
Metro capacity (number/hour)	frequency of metro service*number of coaches in the train*capacity of each coach For this case, capacity is 15*8*160 = 19200 PPHPD (passenger per hour per direction)

(6) Method for calculating output

To calculate several outputs, at first log-sum values for "without metro" condition has been estimated for every income-groups. Log-sum is defined as

$$Logsum = \ln(\sum \exp^{V_{in}}) \tag{10}$$

Where, V_{in} represents the observed part of the utility

The log-sum for "with metro" scenario has also been estimated. Using the log-sum values, User surplus (US) have been calculated for every income group.

User surplus is calculated by taking the differences of log-sum of "with metro" and "without metro" case[22]. This US can be converted to monetary unit by dividing the US by the cost parameter. Equation form of user surplus is

$$US = \frac{1}{\beta_{cost}} \left[\ln\left(\sum \exp^{V_{in}^{1}}\right) - \ln\left(\sum \exp^{V_{in}^{0}}\right) \right] \tag{11}$$

Where,

US= User surplus

$\ln(\sum \exp(V_{in}^{1}))$ = log-sum value after metro has been introduced or "with metro" condition

$\ln(\sum \exp(V_{in}^{0}))$= log-sum before introduction of metro or "without metro" condition

β_{cost} = Cost parameter

Subscript "1" and "0" has been used for "with" and "without" metro condition respectively. Total consumer surplus can be calculated by multiplying the US by total number of commuters in each group and then taking the summation.

$$CS = \sum \left[\tau * \frac{1}{\beta_{cost}} \left\{ \ln\left(\sum \exp^{V_{in}^{1}}\right) - \ln\left(\sum \exp^{V_{in}^{0}}\right) \right] \tag{12}$$

Equation 12 gives the total consumer surplus.

5. RESULTS

(1) Estimation of crowding cost for dummy crowding variables

Crowding costs have been estimated for different income groups as defined in earlier section. Model estimations are shown in Table 5. We have seen in the descriptive statistics of data section that in the sample of low-income group, there is no private car user. So, there were only three alternatives for LIG.

Table 5 Estimated parameters for dummy crowding variables with TT interaction

	High-income Group			Middle-income Group			Low-income Group		
Parameters	Estimate	Rob.std.err.	Rob.t.ratio(0)	Estimate	Rob.std.err.	Rob.t.ratio(0)	Estimate	Rob.std.err.	Rob.t.ratio(0)
asc_metro	3.5640	1.410	2.530	3.6697	1.439	2.550	0.8043	0.590	1.371
asc_bus	1.0249	1.337	0.770	2.8720	1.599	1.800	1.0480	0.550	1.906
asc_privatecar	3.7144	1.257	2.960	11.5843	2.058	5.630	-	-	-
β_traveltime	-0.0244	1.964	-1.240	-0.0109	1.366	-0.800	-0.0001	-1.100	0.012
β_travelcost	-0.0331	0.006	-5.660	-0.0390	0.005	-7.310	-0.0442	-7.310	0.006
β_headway	-0.4218	0.101	-4.190	-0.2119	0.063	-3.350	-0.1739	-2.950	0.059
β_crowding2	0.0039	1.004	0.390	-0.0013	0.780	-0.170	-0.0076	-1.020	0.745
β_crowding3	0.0086	1.581	0.550	-0.0009	0.789	-0.110	-0.0081	-0.950	0.847
β_crowding4	-0.0028	1.290	-0.220	-0.0073	0.820	-0.900	-0.0128	-1.690	0.760
β_crowding5	-0.0302	0.947	-3.190	-0.0229	0.743	-3.090	-0.0327	-3.180	1.027
β_crowding6	-0.1039	1.691	-6.140	-0.0627	1.203	-5.220	-0.0580	-5.020	1.155
sigma_panel1	4.0315	0.762	5.290	3.0654	0.522	-5.870	2.6005	-5.090	0.511
sigma_panel2	3.6475	1.407	-2.590	1.4979	0.517	2.900	0.1727	0.490	0.351
sigma_panel3	10.789	2.441	-4.420	12.775	1.846	6.920	-	-	-

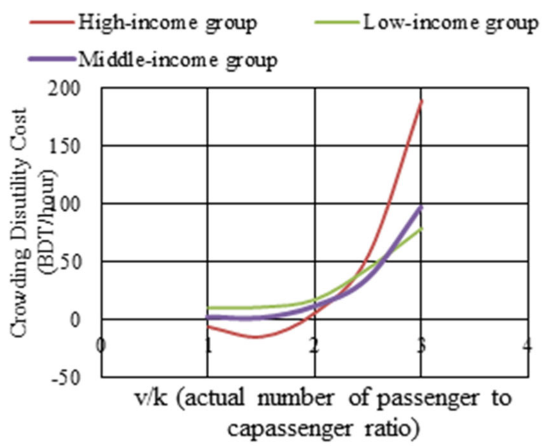

Fig 4 Crowding cost vs. Flow ratio for dummy crowding variable

Crowding variable parameters are found significant for level 5 and 6 for all three groups. But the values are varying for different income groups. From the dummy crowding parameters, crowding costs have been calculated by dividing the crowding parameters by travel cost parameters and expressed as cost per hour. Later, these income group-wise crowding costs have been plotted against the crowding levels. Crowding levels have been expressed as flow ratio. The plot is shown in Fig 4. It is observed that at crowding level 6, the crowding costs are 188.3, 96.5 and 78.7 BDT per hour for HIG, MIG and LIG respectively.

(2) Estimation of crowding cost for continuous crowding effect

The estimation of ρ for different income groups has been carried out using grid-search method. The continuous impact of crowding cost has been estimated for different income groups. It is estimated that for HIG, MIG and LIG the values of ρ that gives maximum likelihood are 6.3, 7.8 and 4. Corresponding values for γ are -0.000122, -0.000013 and -0.000666 respectively. The values of γ are negative in all cases as desired. From the estimated values of γ and , the equations for HIG people is $-0.000122 * (\frac{v}{k})^{6.3}$. The equations for MIG and LIG people are $-0.000013 * (\frac{v}{k})^{7.8}$ and $-0.000666 * (\frac{v}{k})^{4}$

respectively. The corresponding parameters for different income groups are shown in Table 6.

Table 6 Estimation of parameters for continuous crowding impact

	High-income group			Middle-income group			Low-income group		
	Estimate	Rob.std.err.	Rob.t.ratio	Estimate	Rob.std.err.	Rob.t.ratio	Estimate	Rob.std.err.	Rob.t.ratio
asc_metro	4.7239	1.663	2.840	3.5888	1.184	3.030	0.5649	1.433	0.39
asc_bus	1.0669	1.401	0.760	2.7432	1.442	1.900	-0.5892	1.5769	-0.37
asc_privatecar	2.5648	1.659	1.550	8.5197	1.624	5.250	-	-	-
β_traveltime	-0.01589	1.631	-0.970	-0.01324	1.098	-1.210	-0.00612	1.0702	-0.57
β_travelcost	-0.0325	0.007	-4.810	-0.03880	0.005	-8.110	-0.0441	0.0062	-7.1
β_headway	-0.4482	0.094	-4.750	-0.2115	0.057	-3.690	-0.1764	0.0584	-3.02
γ	-0.00012	0.002	-5.820	-0.00001	0.000	-5.760	-0.000666	0.0133	-5
sigma_panel1	3.4857	0.619	-5.630	2.784	0.582	4.780	2.6025	0.5296	-4.91
sigma_panel2	5.6375	1.101	-5.120	2.0512	0.527	3.890	0.2923	0.4722	0.62
sigma_panel3	8.8897	3.465	-2.570	9.9014	1.152	8.600	-	-	-

Crowding cost has been calculated for every income group and plotted against crowding intensities. For LIG, the alternative private car is not available in the SP survey conducted as stated earlier. From the estimated parameters, the crowding costs for different income groups have been calculated for comparison. Fig 5 shows the comparison of crowding cost for different income groups. It is observed that at very small intensities of crowding user of all income groups show little and almost equal sensitivities. With the increase of crowding intensities after passenger flow ratio of 2.5, the difference in group-wise crowding cost sensitivities increases drastically. However, the response curve of crowding cost has sharpest slope for high income group. The slope of crowding cost curve for LIG is flatter compared to high-income group and middle-income group. Middle-income show almost similar slope in crowding cost curve but maintains an offset with the response of high-income group. Similar trends have been observed in case of dummy crowding dimensions.

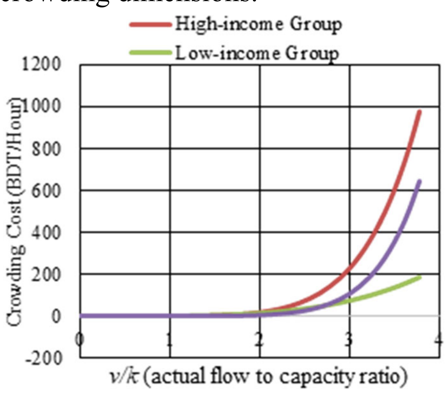

Fig 5 Non-linear crowding cost vs. flow ratio for income group

(3) Results for fare scenario analysis

Number of scenarios has been created as stated in the methodology. Fare has been changed across the scenario. For every scenario log-sum has been estimated. Estimated values for eleven different scenarios are shown in Table 7. These estimated values can be called as "with metro" condition.

Table 7 Scenario-wise log-sum values for different income groups at (with metro) condition

Scenario	Capacity of metro (passenger/hour)	Fare	Log-sum value		
			HIG	MIG	LIG
1	19200	500	-8.630	-4.427	-6.155
2	19200	400	-8.443	-4.426	-6.155
3	19200	350	-8.124	-4.422	-6.155
4	19200	300	-7.583	-4.406	-6.154
5	19200	250	-7.202	-4.362	-6.149
6	19200	200	-7.250	-4.294	-6.126
7	19200	150	-7.604	-4.241	-6.046
8	19200	100	-8.067	-4.260	-5.833
9	19200	50	-8.453	-4.348	-5.456
10	19200	10	-8.622	-4.410	-5.119
11	19200	0	-8.640	-4.418	-5.051

The similar log-sum values for "without metro" scenario has also been estimated as shown in Table 8. As stated in the methodology, user surplus has been calculated by subtracting log-sum of "without metro" condition from the "with metro" condition.

Table 8 Estimated log-sums for different income groups at “without metro" condition

Log-sum values		
HIG	MIG	LIG
-8.6577	-4.4272	-6.1552

For the scenarios above, capacity of metro was kept fixed. However, we can change the capacity to any value as we need. Capacity of metro has been calculated by multiplying number of metros per hour with number of coaches and capacity of each coach. As stated in the general information in the methodology section, the total number of commuters for peak hour is 334081. In the scenarios, headway has been assumed 4 min. So, number of trains per hour is 15. Total 8 cars have been assumed in a metro. The normal capacity of each coach has been assumed as 160. So, the capacity of the train per hour is 15*8*160=19200 PPHPD. To observe the impact of fare on user’s surplus for different income groups, user surplus has been plotted against fare of metro in Fig 6. The values for user surplus at different fare are also shown in Table 9. From the Fig, at very low or zero fare, Consumer of LIG receives highest consumer surplus compared to MIG and HIG. However, with the increase of fare, users of LIG gradually lose their surplus and become zero at a fare of around 250. The trend is opposite for HIG and MIG. With increasing fare, their consumer surplus increases. At a fare of around 150 and 230, consumers of MIG and HIG reaches their peak respectively then further increase of fare their consumer surplus decreases gradually. Total consumer surplus has also been calculated and plotted against fare in Fig 7. It is observed that with the increase of fare from zero, total consumer increases and reaches peak at a fare around 220. Then gradually decreases with further increase of fare.

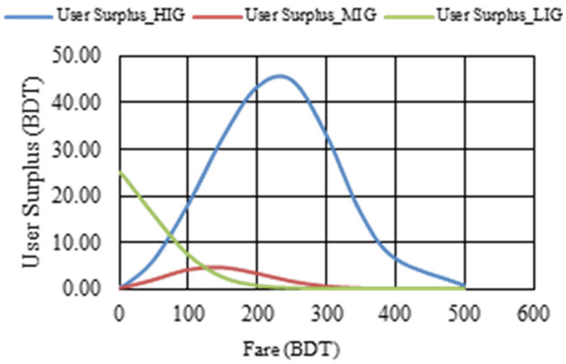

Fig 6 Impact of fare on user's surplus for income group

Table 9 Income group-wise user surplus and total consumer surplus

Scenario	Capacity of metro (passenger/hour)	Fare	Users Surplus			Total CS (BDT)
			HIG	MIG	LIG	
1	19200	500	0.86	0.00	0.00	58854.1
2	19200	400	6.61	0.02	0.00	452951.8
3	19200	350	16.41	0.13	0.00	1133696.1
4	19200	300	33.08	0.56	0.03	2320347.2
5	19200	250	44.79	1.67	0.15	3251006.7
6	19200	200	43.31	3.44	0.66	3359635.1
7	19200	150	32.43	4.80	2.48	2779478.0
8	19200	100	18.18	4.30	7.31	1749594.5
9	19200	50	6.29	2.03	15.85	669280.2
10	19200	10	1.10	0.43	23.50	126460.9
11	19200	0	0.54	0.22	25.04	63659.8

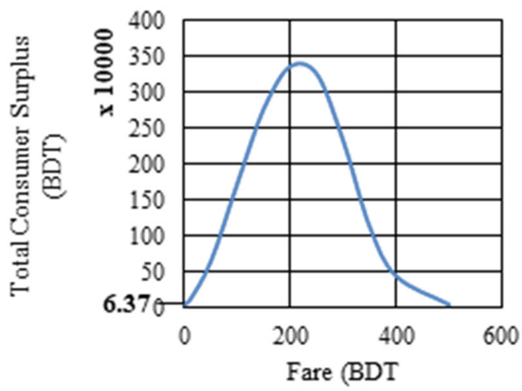

Fig 7 Impact of fare on total consumer surplus

To observe the impact of fare on metro passengers’ demand, income group wise passenger demand has been plotted against fare for different income group in Fig 8.

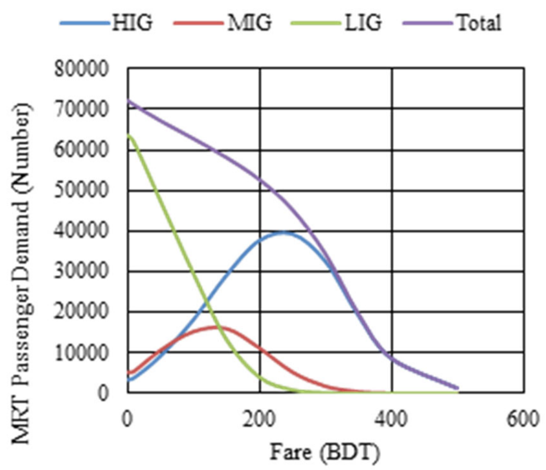

Fig 8 Metro passenger demand distribution for different fare for different income group

From the Fig, it is obvious that users of middle-income and high-income group show very little demand for metro at very low or "zero" fare, but low-income group user show large demand at lowest fare. However, with the increase of fare, demand increases for both HIG and MIG but decreases for LIG. At a fare around BDT of 250, demand for metro becomes zero for LIG. MIG users show increase in demand up to a fare around 150 then start to decrease the demand and becomes zero at around a fare of BDT 320. HIG users continue to increase demand until around 230 and comes to a zero state at a fare around of BDT 500. The total demand curve shows uniform curve for demand against different fares. Total demand becomes zero at around a fare of BDT 500. The response of metro demand to fare is like user surplus vs. fare relation.

6. SUMMARY AND CONCLUSION

This study was conducted for two specific purposes. Firstly, to investigate the heterogeneities crowding sensitivities across the different income group of users to address the disparity among users. Secondly, with the responses from crowding sensitivity analysis, fare scenarios have been analyzed. Results show that there exist heterogeneities in the sensitivities of crowding costs across the income groups and the magnitude of the heterogeneity is not negligible in quantity. As consumers of high-income group's value crowding cost higher than consumers of low-income and middle-income group, a high-level crowding will induce higher disutility to the consumers of HIG. For the case of low-income user, they show flatter response compared to users with higher income, so crowding will not induce a very significant disutility for them compared to other groups. Disutility of crowding has been described in the survey by the facility change in the followings:

- Multi-tasking activities like laptop and mobile browsing, reading newspaper and book etc.
- Movement space inside the vehicle (Physical proximity between passengers)
- Possibility of Getting a seat and,
- Density of standing passenger

Crowding cost heterogeneities might have been coming from the valuation of these activities by the income groups. Many of these multi-tasking activities is not available to the low-income people. With the increase of in-vehicle crowding, facilities to do the multi-tasking diminishes which might impact on the valuing crowding cost by the income groups. As reduction of multi-tasking facility has been stated for every crowding dimension, the user might have taken the fact into account. However, there are many other factors to induce disutility to the metro users which can be investigated. It would be great if we could estimate the impact of other factors and compare with the impact of in-vehicle crowding then it would be possible to know how much attention should be given to the in-vehicle crowding issue by the policy makers. Facilities to do the multi-tasking diminish which might impact on the valuing crowding cost by the income groups. As reduction of multi-tasking facility has been stated for every crowding dimension, the user might have taken the fact into account. However, there are many other factors to induce disutility to the metro users which can be investigated. It would be great if we could estimate the impact of other factors and compare with the impact of in-vehicle crowding then it would be possible to know how much attention should be given to the in-vehicle crowding issue by the policy makers.

We have seen that the effect of fare on consumers surplus and passenger demand is heterogeneous in nature. It is intuitively understandable that people with low income value crowding lowly and thus it does not affect their consumer surplus and demand a lot. Whereas, people with higher income value crowding phenomenon greatly and thus crowding induces great loss on their consumer surplus. Eventually, it impacts their mode choice response. For consumer surplus, it is found that highest consumer surplus doesn't come up with equity. The fare that results in maximum consumer surplus has little contribution from medium or low-income people. This is also true in case of maximum revenue estimation. The fare that yields maximum revenue doesn't come with equity. Capacity change of metro by changing headways or coach capacity have proportional impact consumer surplus but don't have impact on the equity distribution.

As major objective of any kind of public transport system is not only to collect revenue; rather to maximize the consumers' welfare or consumer surplus. In this study, the impact of crowding on different economic class of user has been estimated and based on the responses of crowding, impact of fare on demand distribution; consumer surplus and total revenue have been investigated. It is found that using an "average fare" for transit services without taking the socio-economic disparity into account has the problem of social exclusion bias. So, in setting price of transit services, authority must consider the heterogeneities that arise due to existence of socio-economic disparity across the user. Also, increasing capacity increases the overall consumer surplus for every income group but has no major impact on equity distribution. One possible solution to address this social exclusion bias is introducing differential fare by varying the level of services for the same transit service so that low income user can choose lower service level at lower fare and higher income user can choose the upper service level at higher fare. For example, for the same train there will be some coaches for low fare and some for high fare and these coaches can be separated based on facilities or services inside. This may bring equity and can avoid social exclusion bias.

One important limitation of this research is the data set. The data set doesn't represent the general socio-economic characteristics of the people of Dhaka city. The data set contains respondents with higher income more than the actual proportion and contains lower proportion of low-income people than the actual. Another limitation of this study is the assumption where road congestion has been ignored and bus crowding in bus has been kept fixed across the scenario. Access time, egress time, crowding at station etc. have not been considered in the utility equation which is also a limitation for this study. The study could be more realistic if we could calculate the operators' cost and would take that into the account for welfare calculation. This is important because usually in developing countries, many infrastructures are constructed from the loan from the development agencies worldwide. So, revenue is an important factor to recover that cost. So, in future further study can be done by incorporating other variables mentioned above. Analysis also can be done considering different level of fare by introducing different service level.

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