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Research paper

Environmental sustainability or equity in welfare? Analysing passenger flows of a mass rapid transit system with heterogeneous demand

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ABSTRACT

Comfort could be one of the major factors influencing demand for public transit systems across income groups. Those in the high-income group, typically car owners, value comfort more than those in the traditionally captive low-income group. This paper examines the heterogenous effect of crowding on mode choice and the subsequent demand for mass rapid transit (MRT) system across income groups using stated-preference data collected from Dhaka, Bangladesh. The crowding variable was incorporated into mixed logit models as a Bureau of Public Roads (BPR)-type function, establishing non-linear sensitivity of different income groups to the effect of crowding on mode choice. We then estimate equilibrium passenger flows for different income groups for multiple scenarios based on varying levels of fares and capacity under the stochastic user equilibrium (SUE) condition. The consumer surplus, revenue, and total surplus associated with each scenario were calculated. The findings show that fares that maximize social welfare are not equitable as they result in very low MRT demand among the low-income group. Meanwhile, higher fares result in greater demand for MRT among the high-income group, improved social welfare, and less total car use. These results highlight the trade-off between an equitable public transport system and environmental sustainability.

1. Introduction

During planning for new public transport systems such as mass rapid transit (MRT), the heterogeneities in demand that may arise from socio-economic disparities are often ignored. Such disparities exist across the world but are more evident in developing countries. Service quality, safety, security, and crowding are important attributes determining the attractiveness of a public transport system and could directly influence the ridership. The value people attach to these attributes may depend on their social standing; for example, people with higher incomes may value less crowded situations in public transport systems higher than those with lower incomes. This implies that higher income earners would be willing to pay a higher price for their desired comfort or to reduce their travel time in crowded conditions. In addition, such heterogeneities could influence their mode choice decisions, as the more affluent may prefer private modes such as cars over traveling in a congested public transport system. Understanding such heterogeneities is crucial for better policy decisions. This is partially because there often exist multiple goals for introducing a public transport system, particularly in developing countries, including (1) the improvement of environmental sustainability by reducing car use, and (2) reduction in disparities by providing a better transport option for lower income people. The former could be achieved when car users, who are mostly higher earners (Luke, 2018; Zhao & Zhao, 2020), shift from cars to public transport, while the latter could be achieved when lower income people, who are mostly non-car users, shift from the current mode (probably mostly walking (Chikaraishi et al., 2017)) to public transport. A key ingredient to understanding how a particular public transport service setting, such as fares, affects the achievement of these goals is to consider heterogeneities in demand across different socio-economic

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groups.

Crowding is a major roadblock to public transport systems. The term refers to the congestion either inside vehicles or at the vehicle stations (or on platforms). This study deals with crowding inside vehicles, and henceforth wherever crowding is mentioned in the article, it refers to in-vehicle crowding. Crowding primarily has two dimensions: objective and subjective (Li & Hensher, 2013). The former refers to the actual physical conditions inside the transport vehicle, and there are a range of measures to quantify crowding; standing passengers per square metre, passengers in excess of capacity, load factor, and proportion of seats occupied (with standing passengers per square metre) are a few examples (Li & Hensher, 2013; Tirachini et al., 2013). The second dimension of crowding is the subjective perception of it, as different people may attach different values to crowding. These perceptions can depend upon the actual objective level of crowding, personal and socio-economic characteristics of the traveller, and their previous experiences. Traditionally, value of travel time savings (VTTS) in discrete-choice models of mode choice have been evaluated by estimating the parameters for travel time and travel cost. However, the incorporation of crowding conditions in these models to account for the monetary value of crowding is gaining popularity.

Crowding has also been used as a variable to test its effect on public transport route choice, fare optimisation, waiting time, travel time reliability, and well-being of travellers (Tirachini et al., 2013). Adding crowding variables in transportation models helps to account for the effect of an important predictor variable that affects public transport ridership. However, an area of research that has received insufficient attention is the analysis of the heterogeneities in the effects of crowding owing to socio-economic disparities. The value people attach to crowding could be dependent on their income. There are multiple ways in which this could manifest. First, people belonging to the high-income group might be worried about safety during crowded conditions. Higher risk perceptions related to theft of their precious goods (Hirsch et al., 2016) might increase their crowding valuation. Second, crowded situations might increase their out of vehicle travel time as crowding might lead to higher dwell times at stations. The income elasticity of VTTS has been extensively studied (Börjesson et al., 2012; Mackie et al., 2001). It is well established that VTTS increases with income. Therefore, it is possible that people with high-income would be willing to pay more for a less crowded condition, which might reduce their total travel time. Finally, crowded situations restrict travellers from using their travel time in a worthwhile manner (Varghese et al., 2020) and people with high-income would want to avoid such a situation to be more productive during travel, increasing their crowding valuation. These variations in the value of crowding based on income has been rarely explored while estimating the impact of crowding on public transport ridership. Moreover, these socio-economic disparities are more prevalent in developing economies. Their effects lead to heterogeneities in actual demand for the public transport mode, which is essential for policy-makers to evaluate. Many important policy decisions, such as fare pricing and capacity allocation of public transport services, could be aided if such heterogeneities were well understood.

The aim of this research is twofold. First, we analyse sensitivity to crowding in the mode choice behaviour of travellers based on their income, using stated-preference (SP) survey data collected in Dhaka, Bangladesh. We employ error component mixed logit (ML) models to achieve this objective. Second, we implement a fare- and capacity-based scenario analysis to estimate equilibrium passenger flow and confirm the influence of fare and capacity settings of the Dhaka metro system on the ridership and social welfare of the users. Through the scenario analysis, we obtain equilibrium passenger flows under heterogeneous effects of crowding across different income groups. This allows us to highlight the trade-off between the improvement of environmental sustainability (by the reduction of car use) and the improvement of equity in welfare in a quantitative manner. We believe that this will be a major challenge for policymakers in developing nations, and our quantitative results would help them to put this issue on their policy agenda.

The rest of the article is organized as follows. Section 2 reviews the literature on the treatment of crowding variables in mode-choice models, their role in fare setting, and the evidence from developing countries. Section 3 describes the methodologies adopted in this study. Section 4 describes the study area, survey methodology, and the data for the analyses. Section 5 discusses the results of the ML models. Section 6 discusses the results of the policy analysis and finally, in Section 7 we conclude the paper with a discussion on key findings and contributions and the way forward for this research.

2. Literature review

The treatment of crowding variables in utility equations varies across the literature. There are two distinct aspects to how crowding variables are utilized. First, they vary according to kind of variable or crowding indicator used. Second, the indicator may vary in how it was used, for example, as a continuous or dummy variable, or it was added to the utility equations as an interaction term. This brief review of the literature covers both aspects and identifies gaps in the literature.

Tirachini et al. (2013) estimated five separate mode-choice models (multinomial logit (MNL) and random parameters models) with different treatments of crowding variables in the utility equations. They compared models that included the following variables: 1) no crowding variable; 2) density of standees (in passengers per square metre (pax/m^2)); 3) density of standees and the proportion of seats occupied, assuming that crowding will affect passenger disutility only when at least 25% of the seats are occupied, 4) a load factor above 60%, assuming that crowding will affect passenger disutility only above 60%, and 5) a load factor above 90%, assuming passenger disutility only above 90%. All the crowding variables mentioned above were introduced into the utility equation as interaction terms with travel time, indicating that crowding will cause more disutility if the travel time is longer. Similarly, Yap et al. (2020) introduced two crowding variables into the utility equations of MNL and ML models as interaction terms with travel time. The 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 a similar fashion, the second variable, density (in pax/m^2) for each link and time period was also calculated by taking the weighted average (see Yap et al. (2020) for formulations). In addition, they segmented the models based on whether the passengers were frequent travellers.

Other studies used a combination of the above-mentioned crowding variables. Dummy variables representing only the crowding level, i.e., not an interaction term, were used by Shen and Chatman (2015). Meanwhile, both Björklund and Swärdh (2017) and Whelan and Crockett (2009) used dummy variables representing crowding levels (both when seated and standing) in interactions with travel time. A continuous variable for density and a dummy variable representing whether the passenger was standing were used in the utility equations by Tirachini et al. (2017), while continuous variables representing number of standing passengers and proportion of passengers seated were used by Hensher et al. (2011). In addition, dummy variables representing passenger density with latent variables representing attitudes towards crowding in hybrid discrete-choice models were used by Márquez et al. (2019), whereas Sahu et al. (2018) used a combination of a continuous variable for crowded seat time, dummy variables for standing up to 10 min and standing from 10 to 20 min (at a density of 7–9 pax/m^2), and a continuous variable representing standing time in *super-dense crush load* (13–15 pax/m^2) in the utility equations. Batarce et al. (2016) structured crowding density as a function of individual characteristics, whereas Ho and Hensher (2016) jointly estimated mode and time of day choice by including a continuous variable for crowding representing the number of standing passengers.

The literature on the use of crowding as an independent variable shows no single standard measure. The variables have been used to represent both linear and non-linear relationships with (dis)utility. While it is expected that the disutility from greater crowding will be much higher than it would be at a lower level, the assumptions on the crowding variable and the way it is included in the utility equations may affect the final estimation results.

One of the major purposes of introducing crowding variables into utility equations was to estimate crowding costs. Haywood and Koning (2015) estimated the generalized, marginal, and social cost of using public transport, assuming a linear relationship between crowding density (in pax/m^2) and crowding costs. They endogenized the costs of public transport to the level of usage in a manner analogous to road congestion studies where traffic congestion levels determine travel time. Meanwhile, Tirachini et al. (2013) estimated demand by considering crowding and observed that not considering crowding would lead to overestimation, because crowding causes negative interactions among users. Similar findings regarding the overestimation of demand and user benefits by not accounting for crowding were noted by Batarce et al. (2016). In another study, Tirachini et al. (2014) considered crowding externalities to maximize social welfare while accounting for the interrelationships between traffic congestion and crowding in buses. They showed that optimal bus frequency is very sensitive to crowding costs and overall traffic congestion levels. They also observed that inclusion of crowding externalities results in a sizeable increase in the optimal bus fare and a decrease in the optimal bus subsidy. Similarly, Börjesson et al. (2017) observed that crowding was the main cause of a rise in optimal bus fare during peak hours. In addition, greater crowding discomfort resulted in a higher optimal bus frequency, lower subsidies during peak hours when the car toll remained unchanged, and more road space allocated to bus lanes. De Palma et al. (2017), in their study on trains from Paris, showed that the short-run welfare gains decrease with increased total ridership when optimal time-dependent fares are introduced and when the crowding cost function is convex. These studies succinctly captured the influence of crowding while estimating demand, user benefits, optimal fare, and frequency.

The above-mentioned brief literature review confirms that a number of studies have considered the crowding costs of public transport, but its heterogeneities have been little explored. The argument around ‘crowding cost’ and optimal fares runs the risk of making these systems inequitable. Therefore, it becomes necessary to understand how the consideration of crowding influences demand and user benefits for different socio-economic groups. The heterogenous effect of crowding has been explored previously (Sahu et al., 2018; Tirachini et al., 2017), but its role in policy discourses needs to be explored further. This becomes more important for developing economies with high levels of disparities, where crowding has received limited attention.

Pucher et al. (2005) described the crowding in Mumbai, India’s local trains as a super-dense crush load representing a standing density of more than 12 pax/m^2. The income disparities in these countries make many passengers captive riders of public transportation, leaving them with no choice but to travel in uncomfortable conditions. The studies on crowding in developing countries show how researchers have previously dealt with the variable. Katz and Rahman (2010) presented evidence on the levels of crowding in the buses in Dhaka. They noted that local buses in the city had higher levels of crowding than ticketed buses. Basu and Hunt (2012) observed that train choice behaviour in Mumbai is affected by headway time and ride time associated with crowding level. In addition, they noted that increased crowding resulted in higher VTTS. Sahu et al. (2018) 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) than male passengers. Meanwhile, people with relatively high incomes were more sensitive to the crowding variable, measured by 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. (2018) observed that socio-economic individual variables such as age, gender, income, and education levels influence the WTP for reducing crowding. They also confirmed that marginal disutility for in-vehicle crowding is lower for low-income people, and high-income people tend to avoid riding on crowded public transport.

These studies indicate that the low price of public transport would naturally put a higher priority on low-income people, not only because of the affordable price but also because it would lead to in-vehicle crowding, pushing high-income people away from public transport use. Although low-priced public transport would be a good policy option to reduce mobility disparities across income groups, this is controversial from the perspective of environmental sustainability: a number of studies indicate that reduction of car use is a necessary step to alleviate environmental issues in developing countries (e.g., Kjellstrom et al., 2002; Shalizi & Carbajo, 1994). From this point of view, a higher priority of public transport use should be given to high-income people, who make up the majority of car users in developing countries. We believe that policymakers should have a clear standpoint on this controversial aspect of price setting in their discourse. However, to the authors’ knowledge, few have discussed the results of quantitative analyses to explore the trade-off between improving environmental sustainability (through the reduction of car use) and improving equity in mobility services. This study attempts to fill this gap.

3. Research methodology

This section introduces the methodology of this study. First, we introduce mode-choice models that include the heterogeneous effect of crowding on mode choice across income groups. Second, we introduce a way to utilize this mode-choice model to obtain stochastic user equilibrium (SUE) flows in different fare and capacity scenarios, where crowding introduces interaction effects among heterogeneous users.

3.1. Effect of crowding across income groups

To estimate the heterogeneous effects of crowding on mode choice across income groups, the crowding variable was included in the utility equations in two distinct ways:

1) To confirm empirically the possible non-linear impacts of crowding level on mode choice, crowding dummies were directly incorporated into the utility equations based on the hypothesis that the crowding disutility parameters for higher levels of crowding would be substantially higher. As we had six crowding levels, we incorporated five crowding level dummies into our utility equations, taking level 1 as the reference level (see Table 2). We used an error component ML model to estimate the impact of crowding. The functional form of the utility equation is as follows:

$$U_{tij} = asc_j + \beta_{TT} * TT_{tj} + \beta_{HW} * HW_{tj} + \beta_{TC} * TC_{tj} + \sum_{k=2}^{6} \beta_{CL,k} * CL_{tjk} * TT_{tj} + ec_{ij} + \varepsilon_{tij} \tag{1}$$

where.

$j \in$ {MRT, Bus, Car, Two-wheeler}

U_{tij}: random utility for an individual i choosing an alternative j in SP scenario t

asc_j: alternative specific constant specific for alternative j

β_{TT}: parameter for travel time

β_{TC}: parameter of travel cost

$\beta_{CL,k}$: parameter for crowding level k ($k = 2 \ldots,6$; only for MRT, Bus).

TT_{tj}: travel time for alternative j in SP scenario t

HW_{tj}: headway for alternative j in SP scenario t (only for MRT, Bus).
TC_{tj}: travel cost for alternative j in SP scenario t
ec_{ij}: individual-specific error component for alternative j, following the normal distribution with mean 0 and variance σ^2
ε_{tij}: white noise, following the standard Gumbel distribution
CL_{tjk}: 1: if the crowding level is k for alternative j under scenario t; 0 otherwise

As described later, the models for different income groups were tested with only travel-related alternative specific variables but without socio-economic factors such as age and gender.

2) As described below, the estimated parameters for crowding dummies indicate that Bureau of Public Roads (BPR)-type function could well approximate the identified non-linear effect of crowding on (dis) utility. BPR functions commonly have been used to quantify the relationship between traffic flow and travel time on road networks. Tian et al. (1997), in their study of road traffic assignment in crowded conditions, quantified in-vehicle discomfort costs using a BPR-type function. They formulated the total link travel time t_a as a continuous function of link flow V_a using the following equation:

$$t_a = \alpha_3 t_l^a + \beta_3 \left(\frac{V_a}{K_l^a}\right)^{\rho'} \tag{2}$$

where, t_l^a is the in-vehicle travel time of transit line l on link a and α_3 is a positive parameter associated with t_l^a. K_l^a denote the practical capacity of transit line l on link a and β_3 and ρ' are positive parameters associated with the discomfort inside transit vehicles.

We adopt a similar function and incorporate it in our utility equations:

$$U_{tij} = V_{tij} + ec_{ij} + \varepsilon_{tij} = asc_j + \beta_{TT} * TT_{tj} + \beta_{HW} * HW_{tj} + \beta_{TC} * TC_{tj} + \gamma\left(\frac{v_{tj}}{K_j}\right)^{\rho} * TT_{tj} + ec_{ij} + \varepsilon_{tij} \tag{3}$$

where.
V_{tij}: systematic utility for an individual i choosing an alternative j in SP scenario t
v_{tj}: actual number of passengers in the coach for alternative j in SP scenario t
K_j: capacity of the coach for alternative j
γ: scale parameter associated with crowding disutility
ρ: shape parameter associated with crowding disutility

The ratio $\frac{v_{tj}}{K_j}$ for both MRT and bus was derived based on the survey (see Tables 1 and 2). If the value of v_{tj} (i.e., number of passengers) is smaller than K_j (actual capacity), the train will remain in normal crowding conditions, although there could remain some standing passengers as the normal transit capacity allows. However, when v_{tj} exceeds K_j, the ratio becomes more than 1 and increases the overall crowding disutility. Therefore, the $\frac{v_{tj}}{K_j}$ ratio has a significant impact on crowding cost, which would be obtained by dividing $\gamma\left(\frac{v_{tj}}{K_j}\right)^{\rho}$ by the cost parameter (β_{TC}).

The probability of choosing an alternative is then denoted by

Table 1
Attribute levels for the stated-preference survey.

Variables	Levels
Travel time (min)	30, 40, 50
Fare (BDT)	70, 150, 300
Frequency of services (min)	4, 7,10
Crowding level (as described above)	1, 2, 3, 4, 5, 6

Table 2
Density and occupancy associated with crowding levels.

Crowding level	Density of standing passengers (pax/m^2)	Occupancy level % (v/k)
1	0	20 (0.2)
2	3	100 (1.0)
3	6	150 (1.5)
4	8	200 (2.0)
5	10	250 (2.5)
6	12	300 (3.00)

$$P_{tij} = \int_{ec_{ij}} \frac{a_{ij} \bullet \exp(V_{tij} + ec_{ij})}{\sum_{j=1}^{J} a_{ij} \bullet \exp(V_{tij} + ec_{ij})} f(ec_{ij}|\sigma) \mathrm{d}ec_{ij} \tag{4}$$

where.
P_{tij}: probability of an individual i choosing an alternative j in SP scenario t
a_{ij}: availability of alternative j for individual i
$f(\bullet)$: normal distribution with mean 0 and variance σ^2

Note that we assume that available alternatives do not change before and after the implementation of MRT for each individual, i.e., availability dummies are generated for each alternative based on their revealed preference (RP) response.

Because simultaneously estimating ρ and γ would make the estimation results unstable, we employ a grid search approach to estimate the parameters. Specifically, given a value of ρ, which varies over a range of values, we estimate γ and other parameters. We select the model that produces the highest maximum log-likelihood value as the final model.

3.2. Fare and capacity scenario analysis

A scenario analysis was conducted by varying the fare and the capacity of the MRT system. For every scenario, the equilibrium flow, consumer surplus, and total revenue were calculated. The equilibrium flows for each income group were calculated using the SUE approach, which was solved using the method of successive averages (MSA). MSA is widely used for calculating the equilibrium flow in traffic networks, and an important characteristic of this method is that it has a decreasing step size at each iteration (Mounce & Carey, 2015). The flow at each iteration can be denoted as

$$x_{n,m} = x_{n-1,m} + \frac{1}{n}(y_{n-1,m} - x_{n-1,m}) \tag{5}$$

where.
$x_{n,m}$: metro flow at the n-th iteration for the m-th income group. Note that a value of $x_{0,m}$ needs to be given at the first iteration. The actual number of passengers in the coach v can be obtained by dividing $x_{n,m}$ by the number of coaches.
$y_{n-1,m}$: updated metro flow obtained from $P_{ti,MRT}(x_{n-1,m})\tau_m$, where τ_m represents the total number of commuters belonging to income group m.

The iterations are continued until total passenger flow $x_n = \sum_{m=1}^{M} x_{n,m}$ reaches an equilibrium value.

We then utilize the equilibrium flow values to calculate user surplus and revenue. The average log-sum of income group m can be denoted as

$$LS_m = \frac{1}{I}\sum_{i=1}^{I}\int_{ec_{ij,m}} \ln\left(\sum_{j=1}^{J} a_{ij}\exp(V_{ij,m} + ec_{ij,m})\right) \mathrm{d}ec_{ij,m} \tag{6}$$

where $V_{i,j,m}$ is the observed part of the utility for individual i choosing alternative j and belonging to income group m.

Average user surplus for income group m can be then calculated for the equilibrium flows using the following formulation:

$$US_m = \frac{1}{\beta_{TC}}\left[\frac{1}{I}\sum_{i=1}^{I}\int_{ec_{ij,m}} \ln\left(\sum_{j\in\{\text{MRT,Bus,Car,Two-wheeler}\}} a_{ij}\exp\left(V_{ij,m} + ec_{ij,m}\right)\right)dec_{ij,m} - \frac{1}{I}\sum_{i=1}^{I}\int_{ec_{ij,m}} \ln\left(\sum_{j\in\{\text{Bus,Car,Two-wheeler}\}} a_{ij}\exp\left(V_{ij,m} + ec_{ij,m}\right)\right)dec_{ij,m}\right] \tag{7}$$

The total consumer surplus can be calculated as

$$CS_{total} = \sum_{m=1}^{M}\tau_m US_m \tag{8}$$

The calculations were made by varying the levels of fare and capacity (a function of headway and number of cars), and finally revenue for each scenario can be calculated as

$$Revenue = \sum_{m=1}^{M}\widehat{x}_m \times fare_{metro,m} \tag{9}$$

where $\widehat{x}_m$ is an equilibrium metro flow for income group m, and $fare_{metro,m}$ is the fare of metro for income group m.

4. Study area, survey, and data description

4.1. Study area

The Government of Bangladesh and the Japanese International Cooperation Agency (JICA) proposed the Revision and Updating of the Strategic Transport Plan for Dhaka (RSTP) (JICA, 2015). A major component of the study was to develop a concept plan for the MRT network in Dhaka, the capital city of Bangladesh. For this study, we choose MRT line 6 (as proposed in the RSTP), which is under construction and expected to commence operations from 2022. The line connects Ashulia with Kamalapur via Uttara Phase 3, Pallabi, Tejigaon, and Motijheel. Motijheel is one of the major central business districts (CBD) of Dhaka with a high concentration of business and workplaces. From this line, we set the origin and destination of our survey and interview people living in Uttara Phase 3 and working in Motijheel, the former being a residential area. Fig. 1 shows the location of the survey respondents with dots showing their homes and work locations.

Dhaka is one of the most populous cities of the world, with a population of 20.3 million (Bangladesh Bureau of Statistics, 2011), which is expected to exceed to 31.0 million by 2035. Its population density is much higher than that of other megacities of the world such as Tokyo or Shanghai (Gallagher, 2016). This has led to a severe traffic congestion problem on the roads and its limited public transport system. The RSTP proposed new MRT lines to relieve this congestion. However, the metro system could also be plagued by overcrowding, which could eventually impact ridership. In addition, Bangladesh is a country with a high level of poverty and income disparity. Chowdhury and Hossain (2018) noted that 24.3% of Bangladesh's total population lived below poverty lines, and even though the country's economic growth had accelerated and there have been major efforts to reduce poverty, income disparity has increased, and in urban areas it has been observed to be higher than in rural areas. Such inequalities would result in severe heterogeneities in the demand for a new MRT system, but such heterogeneities are often not accounted for. Crowding would have different effects on people of different income groups, which could cause variations in demand for MRT systems. MRT systems are expected to play an important role in reducing on-road congestion and subsequently in reducing environmental pollution. However, there is a possibility that car owners may not choose to travel in MRT owing to severe crowding. In the next sub-section, we describe the survey methodology adopted for the study.

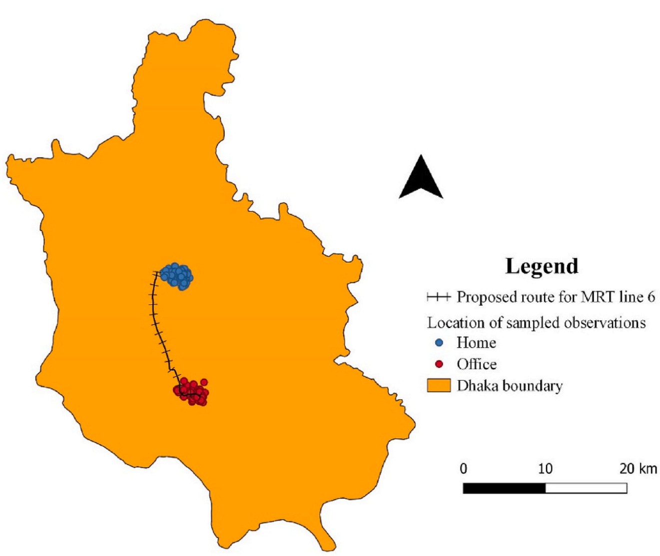


Fig. 1. Study area: Sampling locations in Dhaka.

4.2. Survey design

A face-to-face interview survey was conducted with prospective MRT users living in the Uttara Phase 3 area of Dhaka city (see Fig. 1). A total of 416 people were interviewed. After the data cleaning process, the total number of individuals retained is 361. Four alternative specific attributes namely travel time, fare, frequency of service, and crowding were utilized in an SP design to capture their influence on mode choice utilities. Table 1 lists the levels considered for each attribute. By applying an orthogonal design (specifically, L18 orthogonal array was used. See Grömping, 2018 and Hedayat et al., 1999 for details on experiment designs using orthogonal arrays), we obtained a total of 18 SP scenarios, of which six were presented to every person randomly. Fig. 2 elaborates the data cleaning process employed in this study. Individual specific information on income or location (their home and office locations) were unavailable for 55 people who made 330 SP choices. These responses were removed from the final sample. The questionnaire also included a RP section concerning the characteristics of respondents' commute trips. The RP information was then used to create alternative specific variables for other available modes. The SP part asked the respondent to choose between MRT and their 'usual' mode, reported in the RP part. Trip level information on the alternative specific variables for usual modes of bus, car, two-wheeler (such as crowding level on bus) was missing for 41 SP choices made by 26 people. These also include a few samples when the above mentioned four usual modes were not chosen and some other modes such as taxis were chosen. Because of the very low sample size and unavailable trip-level information, they were not considered in the analysis. Finally, a total of 2125 responses were recorded for 361 respondents after the data cleaning process.

Crowding variables were introduced to the respondents using SP cards, where a description of the crowding was provided using images of the physical conditions associated with each level (the same images are reproduced in Fig. 3). In addition, the respondents were informed about the objective values attached to each level of crowding, i.e., density of standing passengers (pax/m^2) and occupancy level (in percentages and fractions of the capacity). Table 2 lists the same details. Additional information on freedom of movement and the ability to perform multitasking activities associated with each level of crowding was also provided so that the respondents could imagine the situation clearly.

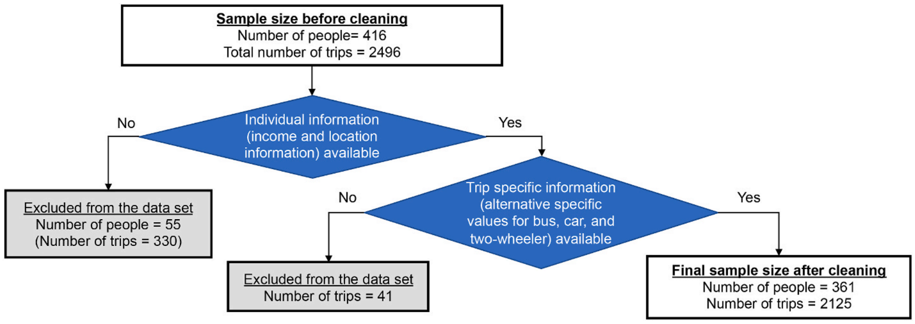


Fig. 2. Data cleaning process.

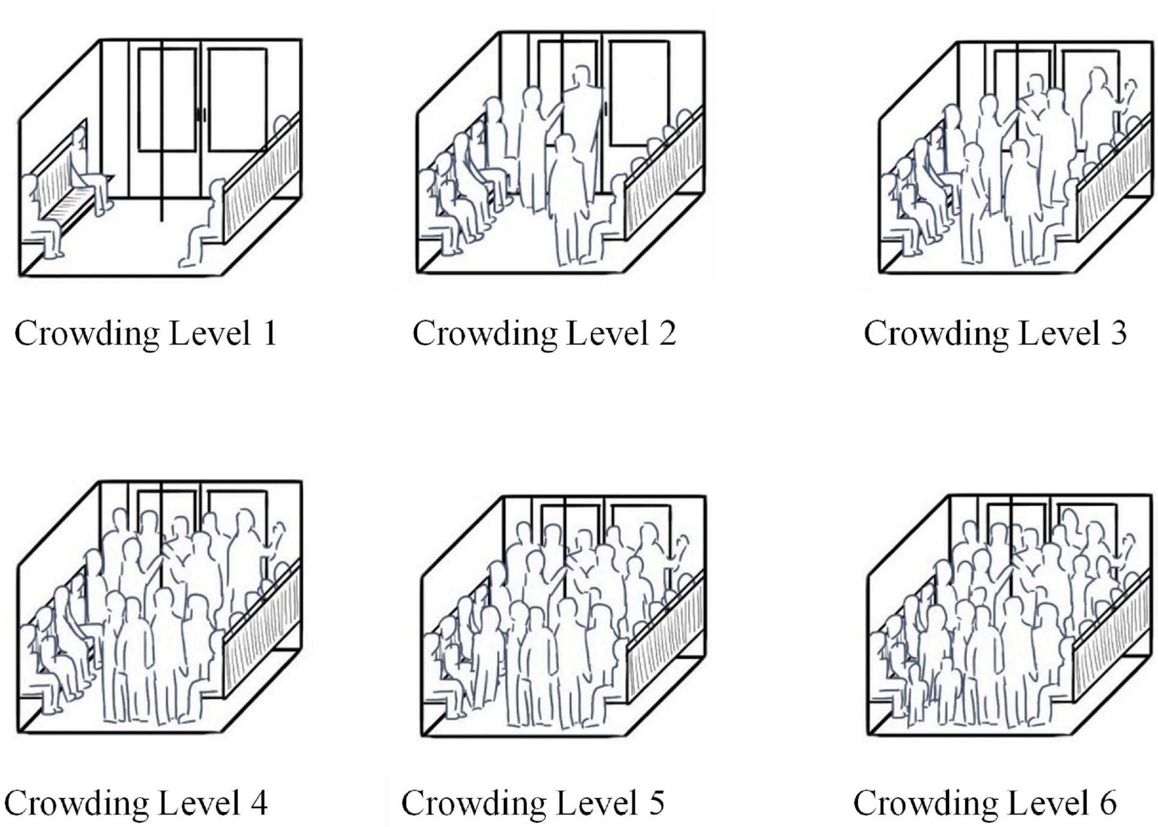


Fig. 3. Graphical representation of crowding levels.

4.3. Data description

A total 361 people were interviewed, and information on their socio-economic status was recorded. The majority of respondents were men (86.15%). Bangladesh Bureau of Statistics (2018) had noted that even after a significant growth in women participation over the last few years, the total percentage of women in active workforce remained considerably lower than men. Meanwhile, the average age of the respondents was noted to be 38.79 years. Data on the income of respondents were also captured, and a considerable amount of skewness was observed in the data towards relatively higher income groups. Based on the low sample size obtained from very low-income groups, the respondents were grouped into the following three groups: 1) the low-income group, with monthly household incomes of less than 50,000 BDT (23.8% of respondents); 2) the middle-income group, with monthly household incomes between 50,001 and 100,000 BDT (39.89% of respondents); 3) the high-income group, with incomes of greater than 100,000 BDT per month (36.29% of respondents) (see Table 3). We understand that our definition for low income group has a higher monthly income than the usual definitions adopted previously (Ministry of Finance, 2022). The average monthly income in the urban areas of Bangladesh was reported to be BDT 22,600 (Ministry of Finance, 2022) whereas, the respondents in our survey were skewed towards the relatively higher income cohorts (76.18% of the respondents earned more than BDT 50,000). Possibly because the area we selected for the survey, i.e., Uttara Phase 3, is a satellite town to accommodate relatively high-income earners (Rashid, 2002). Nevertheless, we believe that by segmenting our analysis into the aforementioned three groups, we can understand the heterogeneities in sensitivity to crowding and demand for MRT.

Information on the respondents' current travel behaviour was also collected. It was observed that 75.90% of the current commute trips were made by bus, whereas 15.79% and 8.31% of the trips were made by car and two-wheeled private vehicles, respectively. We also observed some respondents using paratransit modes such as taxis or shared CNG auto-rickshaws; however, there were too few observations of those modes, so they were removed from the analysis. It was also observed

Table 3
Data description.

Variable	Value
Gender	[Percentage of 361]
Male	86.15
Age	[Average (Std deviation)]
Age in years	38.79 (10.67)
Income group	[Percentage of 361]
≤ 50,000 BDT (low-income group)	23.82
50,001–100,000 BDT (middle-income group)	39.89
> 100,000 BDT (high-income group)	36.29
Present commuting mode: Fare (BDT)	[Average (Std deviation)]
Bus	83.99 (29.13)
Car	362.12 (166.42)
Two-wheeler	91.13 (34.39)
Current commuting mode: Travel time (min)	[Average (Std deviation)]
Bus	115.65 (23.94)
Car	105.53 (25.17)
Two-wheeler	86.45 (18.03)
Present commuting mode: Headway (min)	[Average (Std deviation)]
Bus	11.16 (5.13)
Present commuting mode: Bus crowding	[Percentage of 326[a1]]
Level 1	2.15
Level 2	28.83
Level 3	27.30
Level 4	23.93
Level 5	13.50
Level 6	4.29
Present commuting mode choice	[Percentage of 361]
Bus	75.90
Car	15.79
Two-wheeler	8.31
SP commuting mode choice	[Percentage of 2125]
MRT	48.52
Bus	42.45
Car	4.61
Two-wheeler	4.42

[a] 1Percentage of respondents calculated for 326 people for whom buses were available.

that the respondents traveling by bus had a higher mean travel time (115.63 min) compared with those traveling in cars and two-wheelers (105.53 and 86.45 min, respectively). Meanwhile, the average fare was observed to be higher for people who used cars (362.12 BDT) than for those who used buses and two-wheelers (83.99 and 91.13, respectively). The average headway for buses was observed to be 11.16 min (see Table 3).

The respondents were also asked to report on the current levels of crowding experienced on buses. The same levels of crowding used in the SP part of the survey were also used here. It was observed that only 2.15% experienced level 1 of crowding, which meant they could find a seat on the bus. Of the respondents, 28.83% reported that they experienced level 2 crowding, i.e., an occupancy level of 100%, while others reported more than 100% occupancy. Moreover, 27.30%, 23.93%, 13.50%, and 4.29% of the respondents reported crowding that indicated 150%, 200%, 250%, and 300% occupancy levels, respectively (see Table 3). It may be seen that crowding is very common on the buses of Dhaka, and given the high proportion of bus users, it is important to understand people's views of crowding and how these are reflected in their travel mode choice.

Based on the levels of attributes in the SP questionnaire, the respondents were asked to choose between their present mode and MRT, and 48.52% of the respondents chose to travel by MRT. Meanwhile, 42.45%, 4.61%, and 4.42% of the respondents chose bus, car, and private two-wheeler vehicles, respectively (see Table 3).

5. Results: income sensitivity to crowding

5.1. Crowding as a dummy variable

Table 4 and Fig. 4 show the estimation results of the mode-choice model with dummy variables for crowding, which is introduced to confirm empirically the non-linear effects of crowding on utility. The signs of travel time, fare, and headway are on the expected lines. Both Table 4 and Fig. 4 show variations in the effect of crowding as the level of crowding increases from 2 to 6. The non-linearity in the effects is evident, because with increased crowding, there is a nearly exponential rise in the parameter value.

The segmentation based on income groups shows that at crowding level 6, the crowding costs are highest for the high-income group, followed by the middle- and low-income groups. However, it should be noted that the parameter estimates for levels 2 to 4 were not significant for any income group. In the next sub-section, we estimate the ML models by treating the crowding variable as a BPR-type function in the utility equations.

5.2. Crowding as a continuous variable

To estimate the mode-choice model with the use of a BPR-type function for crowding effects, we first performed a grid search analysis to identify the optimum value for ρ for each income group. The ρ value that provided the highest log-likelihood value was selected to estimate other parameters. Values of 6.3, 6.1, and 4.0 were observed to produce the highest log-likelihood values for high-, middle-, and low-income groups, respectively. Meanwhile, for the whole sample, a ρ value of 7.3 produced the highest log-likelihood value.

Table 5 shows the results of the ML model. The parameter estimates for travel time, fare, and headway show the expected signs. Fig. 5 shows the crowding cost, which is obtained by dividing the value of $\gamma\left(\frac{v_{tj}}{K_j}\right)^{\rho}$ by the cost parameter. Similar to the results of the models with crowding levels as dummy variables, the costs of crowding were observed to be highest for the high-income group, especially at higher levels of occupancy $\frac{v_{tj}}{K_j}$. The findings are understandable as people with higher incomes would be more willing to pay for their comfort or to reduce their travel time in crowded conditions. In addition, as the level of crowding increases, the cost associated with crowding increases, given the exponential nature of the BPR-type function.

6. Policy discussions: fare and capacity scenario analysis

The scenario analysis was performed with both the same and differential fares across different income groups. We do not elaborate on how the differential fare system would be implemented but assume that it would be a mechanism such as selling a discount ticket to low-income people or having coach-based variations in pricing. Table 6 lists the details of the scenarios and the set of assumptions made for the analysis. A total of 26,620 (4 levels of headway × 5 levels of number of cars × 11 × 11 × 11 levels of fares for high-, middle-, and low-income groups) scenarios were tested that included both the same and differential fare structures for the different income groups.

A stochastic equilibrium condition was used to calculate the equilibrium metro flow, consumer surplus, revenue, and total surplus associated with each scenario. The scenario analysis was performed for peak hour MRT usage. The headway for the MRT system was varied across the four levels signifying the frequency of the service. The levels considered for the scenario analysis were 2, 4, 6, and 10 min. Meanwhile, the number of cars in a typical metro train was varied across five levels: 4, 6, 8, 10, and 12 cars. The combinations of the headway levels and the

Table 4
Mode-choice model with dummy variables for crowding.

	High income		Middle income		Low income		Whole sample	
	Estimate	t stat	Estimate	t stat	Estimate	t stat	Estimate	t stat
Asc MRT	4.00	2.21	3.60	2.72	0.81	0.72	2.63	3.46
Asc Bus	0.79	0.42	2.60	1.97	1.05	0.49	1.48	1.92
Asc Car	3.32	2.32	12.69	7.87	–	–	6.25	5.72
Asc Two-wheeler	0.0	–	0.0	–	0.0	–	0.0	–
Travel time	−1.11	−1.15	−0.48	−0.65	−0.01	−0.68	−0.58	−1.17
Fare	−0.03	−8.19	−0.04	−10.44	−0.04	−6.69	−0.04	−16.03
Headway	−0.44	−4.75	−0.21	−4.44	−0.17	−3.10	−0.24	−7.67
Crowding level 2	0.32	0.44	−0.10	−0.20	−0.46	−0.67	−0.14	−0.42
Crowding level 3	0.54	0.73	−0.09	−0.17	−0.49	−0.71	−0.18	−0.51
Crowding level 4	−0.31	−0.42	−0.51	−0.93	−0.77	−1.1	−0.45	−1.32
Crowding level 5	−1.98	−2.63	−1.40	−2.63	−1.96	−2.26	−1.39	−3.87
Crowding level 6	−6.52	−5.47	−3.77	−4.65	−3.48	−3.87	−4.02	−7.75
Sigma MRT	3.50	4.75	2.95	4.62	2.60	4.7	3.00	7.84
Sigma Bus	5.39	5.06	1.72	1.85	0.18	0.16	1.39	2.05
Sigma Car	7.05	5.80	8.71	8.75	–	–	12.82	11.57
LL0	−600.392		−651.091		−366.009		−1617.492	
LL final	−305.729		−388.428		−177.545		−929.585	
AIC	639.46		804.86		379.09		1887.17	
No. of individuals	124		151		86		361	
No. of observations	729		882		514		2125	

Asc = alternative specific constant.

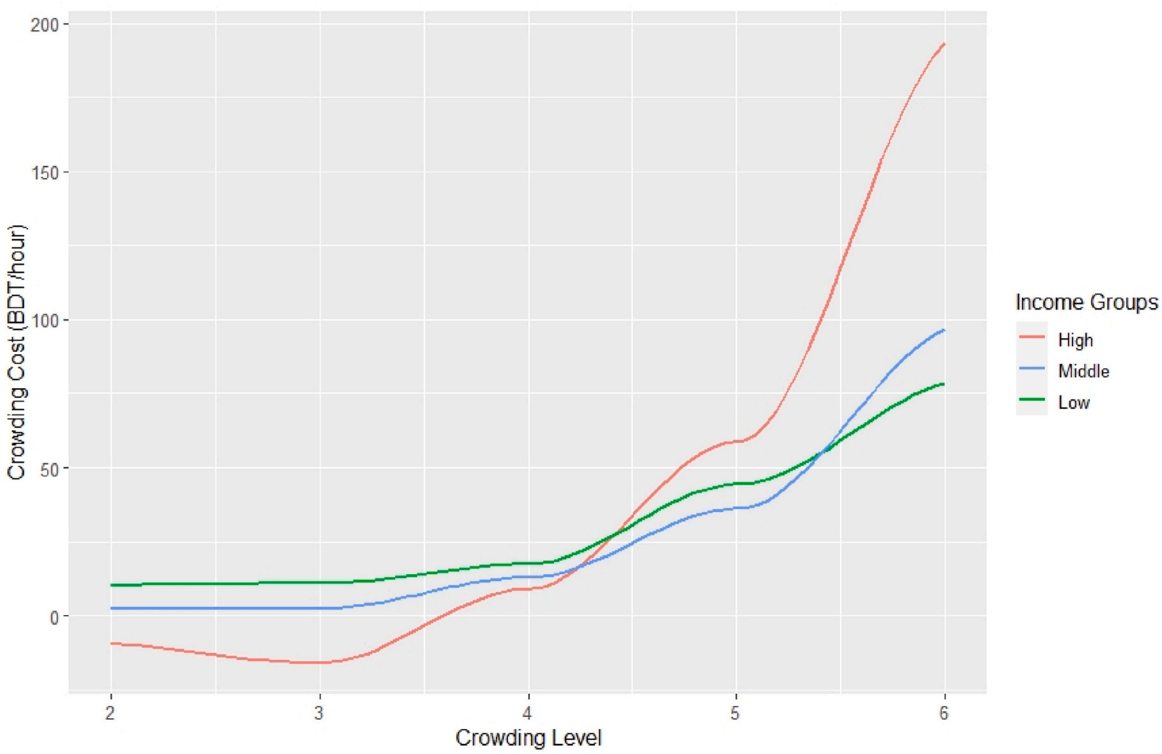


Fig. 4. Crowding cost based on income group when crowding is treated as a dummy variable.

number of cars resulted in 15 unique levels of capacity for which the equilibrium flows were calculated. The fares associated with the MRT system were also varied across the scenarios. First, a scenario with equal fares for all income groups and coaches was varied across 11 levels (see Table 6). Second, the flows were calculated for scenarios with variable fares for each income group (varied across the same 11 levels). Finally, due to the unavailability of data on road congestion levels we ignore its impact in the policy analysis. This is a major limitation of this study as the use of metro will eventually impact the level of congestion on roads and contrarily, congestion on roads will also have an impact on metro ridership. However, in this study we do not consider these impacts.

Figs. 6, 7 and 8 show the distribution of equilibrium flow, consumer surplus, and revenue, respectively, with the varying levels of capacities and fares when the fares are constant across income groups. Meanwhile, Table 7 shows a summary of the scenario analysis illustrating the cases that produced the maximum MRT flow, minimum car flow, consumer surplus, revenue, and total surplus values for both similar and varying fares across income groups.

Notes: Abbreviation: MRT: Mass rapid transit system, HIG: high-income group, MIG: middle-income group, LIG: low-income group; car flow represents the total car usage for all income groups.

Fig. 6 shows equilibrium metro flows for each income group,

Table 5
Mode-choice models with a continuous variable for crowding.

	High income		Middle income		Low income		Whole sample	
	Estimate	t stat	Estimate	t stat	Estimate	t stat	Estimate	t stat
Asc MRT	4.32	2.85	3.67	3.41	0.57	0.47	2.90	4.44
Asc Bus	1.30	0.74	2.87	2.83	−0.59	−0.45	1.60	2.36
Asc Car	3.11	1.99	8.84	3.94			4.72	4.95
Asc Two-wheeler	0.0	–	0.0	–	0.0	–	0.0	–
Travel time	−0.73	−0.94	−0.66	−1.14	−0.37	−0.50	−0.74	−1.8
Fare	−0.03	−8.14	−0.04	−10.28	−0.04	−6.79	−0.04	−16.19
Headway	−0.43	−5.10	−0.22	−4.37	−0.18	−3.19	−0.24	−7.69
Gamma (γ)	−0.0068	−6.77	−0.0046	−6.27	−0.0399	−4.95	−0.0013	−9.71
Sigma MRT	3.42	5.25	2.78	5.71	2.60	4.71	2.81	8.36
Sigma Bus	5.33	5.52	1.93	3.24	0.29	0.26	2.06	4.70
Sigma Car	7.12	6.08	10.04	7.24			10.15	11.95
LL0	−600.392		−651.091		−366.009		−1617.492	
LL final	−306.150		−387.712		−178.407		−925.093	
AIC	632.3		795.42		372.81		1870.19	
No. of individuals	124		151		86		361	
No. of observations	729		882		514		2125	

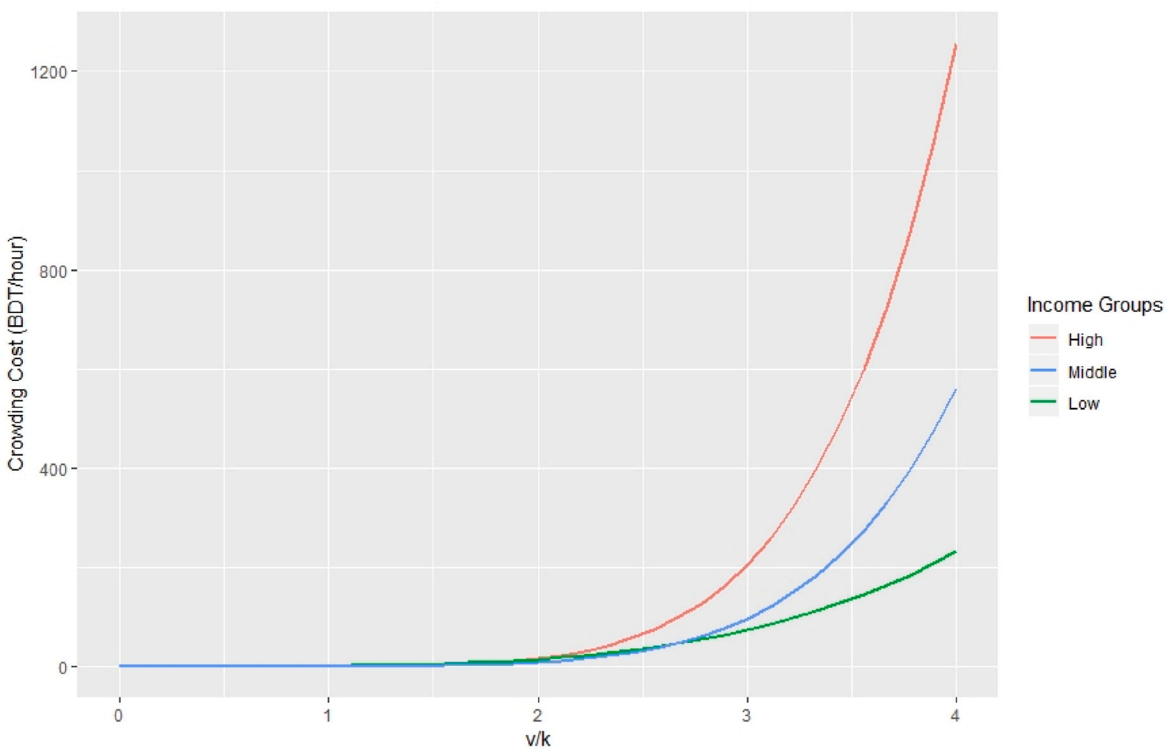


Fig. 5. Crowding cost based on income when crowding is treated as a continuous variable.

confirming the flow for each income group varies depending on the fares for the MRT system. In addition, the figure shows variation in equilibrium car flow based on the MRT fare. The maximum flow for the low-income group is highest when the fare is lowest. In addition, it could be observed that for all capacities, as the fare increases, the equilibrium flow for the low-income group decreases. By contrast, for the middle-income group, there is first a short gradual increase in the flow values as the fare increases, then the shape of the curve is similar to that of the low-income group, i.e., decreasing with an increase in fares. The shape of the curves was observed to be similar across different MRT capacity levels. For the high-income group, it can be seen that for all capacities, the equilibrium flow for the income group first increases with fare and then gradually decreases for higher levels of fare. These differences in the relationship between MRT flow and fare across the three income groups are a result of differences in sensitivity to crowding. People with higher incomes prefer to travel in less crowded conditions and do not mind paying a higher fare for a comfortable commute. Therefore, the highest levels of flow for the high-income group were also observed for higher fares, in the range of 150–250 BDT. The results also indicate that the level of fare for which the highest ridership is observed gradually shifts to lower levels of fare with increased capacity.

An interesting point to note is the way the car flow changes with increased fares. The link is very clear: an increase in high-income MRT use results in a decrease in car use. It can be observed that the car flow decreases (it is lowest in the range of 150–250 BDT) with increased fares and then again increases. This is understandable, as owning and using cars in developing countries is linked to income (Varghese & Jana, 2019).

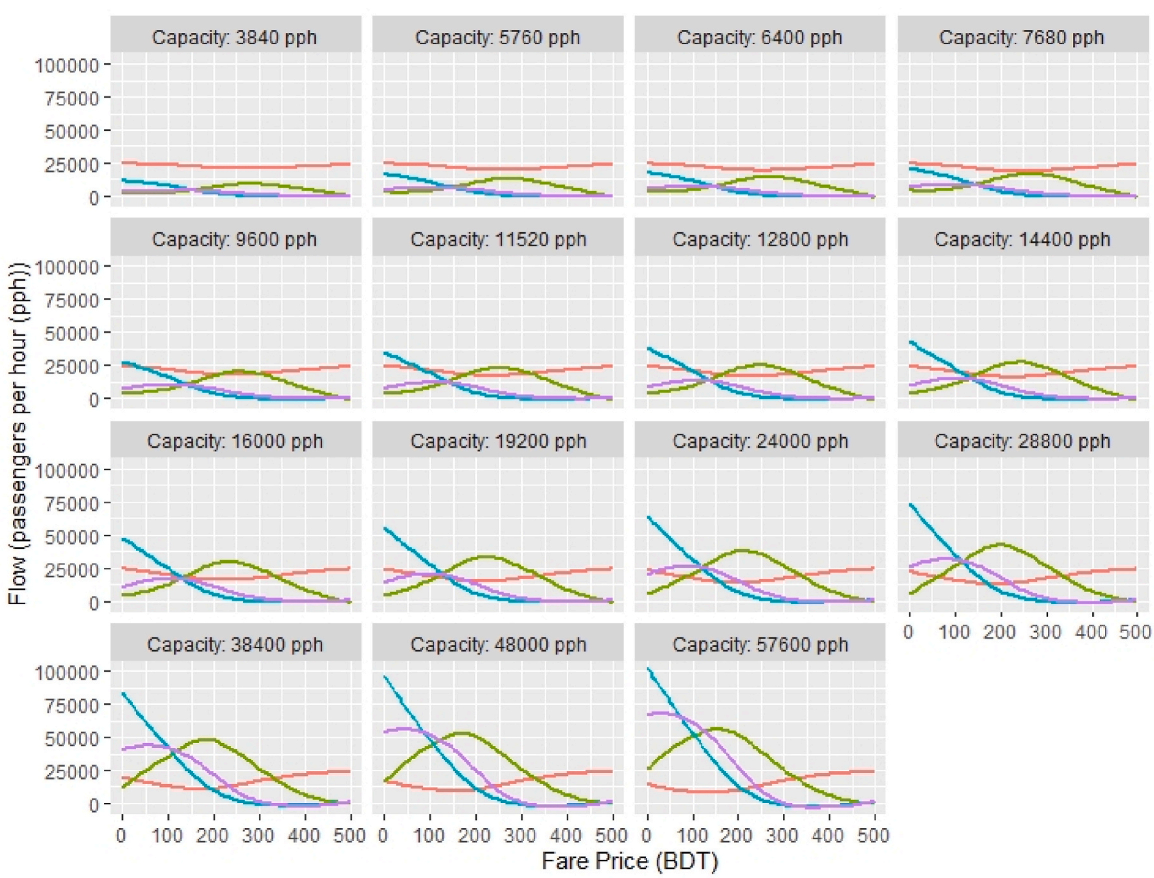
The analysis and the calculation of the equilibrium metro flow based on income group highlight the need to account for the trade-offs

Table 6
Levels of scenarios and list of assumptions.

Item name	Item description
Capacity	$= \frac{60}{headway_{metro}} \times no.\ of\ cars \times 160\ headway_{metro}$ varies between 2, 4, 6, and 10 min *no. of cars* or coaches varies between 4, 6, 8, 10, and 12
Fare	Fares for each income group vary between 0, 10, 50, 100, 150, 200, 250, 300, 400, 450, and 500 BDT
Peak hour passengers (pph, number)	334,081 (JICA, 2015)
Distribution of passenger based on income groups (number)	Low-income group (LIG) (44.10%) = 147,330 Middle-income group (MIG) (35.50%) = 118,599 High-income group (HIG) (20.40%) = 68,153
Bus capacity (number/hour)	It is assumed that bus services will maintain crowding of 150% for all scenarios.
Road congestion	Road congestion has been ignored, i.e., we assume that congestion is not greatly affected by the use of the metro.

between equity considerations and the possibility of reducing private vehicle usage in policy decisions. Additional analyses of total consumer surplus, total revenue, and total surplus further demonstrate the need to discuss these trade-offs. Fare planning in public transport systems often considers the maximization of social welfare, which is usually the sum of producer benefits and user benefits (Borndörfer et al., 2012). User benefits in this study were calculated using the consumer surplus through the *logsum* measure. Moreover, producer benefit is the profit to the public transport provider and is the difference between revenue and cost. In this study, as the cost associated with the provision of MRT is unknown, the revenue generated for different scenarios was calculated. Similarly, total surplus is also represented by the sum of consumer surplus and revenue. Table 7 shows the variation in total consumer surplus, revenue, and total surplus based on capacity and fare levels. The implementation of an optimal fare often ensures that resources are efficiently utilized, costs and benefits are internalized in user decisions, and sufficient revenues are generated (Hörcher & Tirachini, 2021). However, in this case, it can be seen that welfare maximization may lead to optimal fares that result in very low levels of ridership among the low- and middle-income groups.

Figs. 7 and 8 show the variations in total consumer surplus and revenue based on capacity and fare level, respectively. It may be observed that consumer surplus increases with capacity. The consumer surplus values were highest for the lowest fares. However, the graphs for the consumer surplus show a bump, an increase from the usual decreasing trend in the fare range of 150–250 BDT (see Fig. 7). Meanwhile, revenues were also observed to be maximum for the same fare range, i.e., 150–250 BDT (see Fig. 8). Therefore, the calculation of optimal fares considering the maximization of social welfare may produce fares that are not equitable for everyone, as the same fare range produces very low levels of ridership (equilibrium flow values in Fig. 6) among middle- and low-income MRT users. Previous studies have utilized welfare maximization to estimate optimal fares and have observed that low fares result in high levels of welfare (Jin et al., 2019). However, this may not always be the case when comfort variables such as



Notes: Abbreviation: MRT: Mass rapid transit system, HIG: high-income group, MIG: middle-income group, LIG: low-income group; car flow represents the total car usage for all income groups.

Fig. 6. Equilibrium flow across different MRT capacities and fare structure.

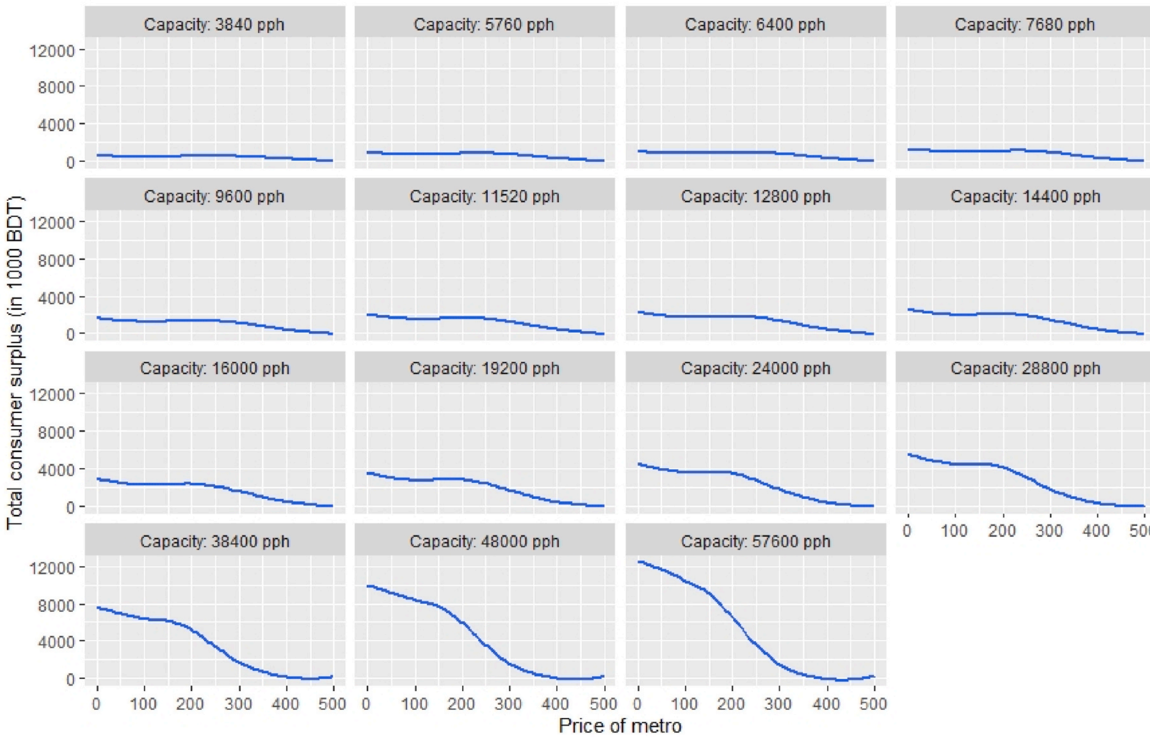


Fig. 7. Total consumer surplus across different MRT capacities and fare structures.

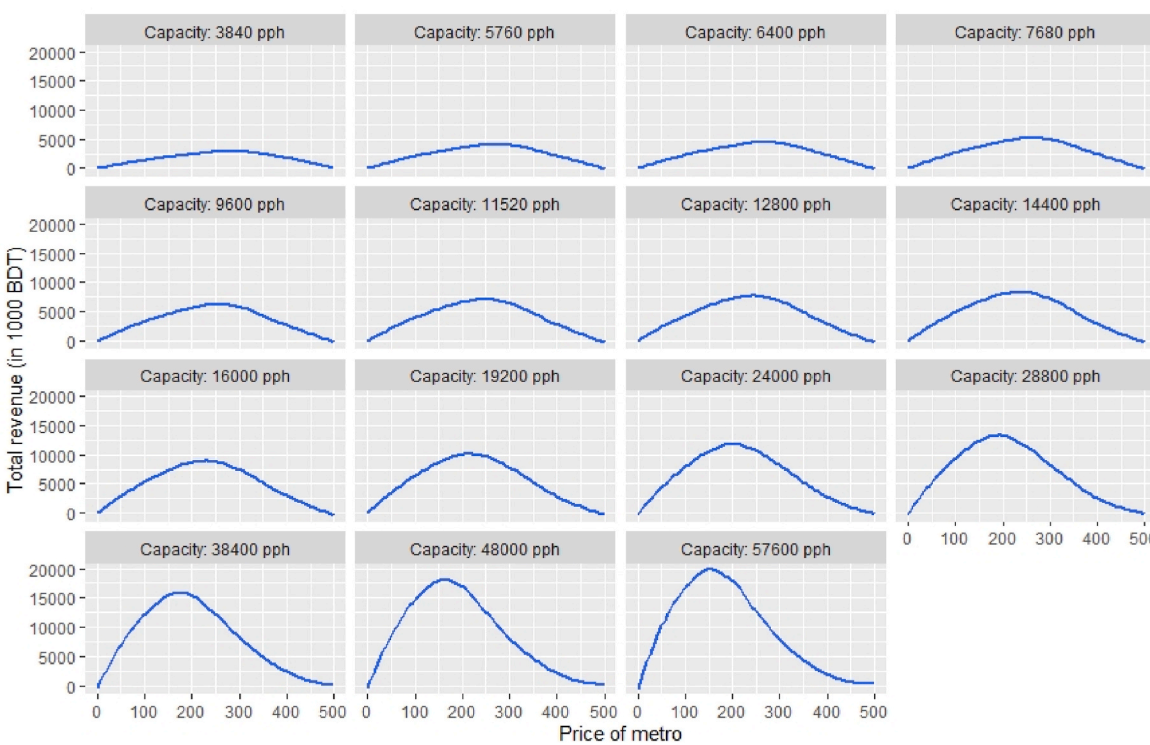


Fig. 8. Total revenue across different MRT capacities and fare structures.

crowding are accounted for in the utility equations and the heterogeneities resulting from income disparities are considered. In addition, the utilitarian maximization of welfare, which focuses on achieving the greatest good for the greatest number of people, has been criticized because it does not clearly specify how welfare will be distributed among people (Pereira et al., 2017).

Fares are a major source of income for transport operators, and generally when fares are increased, ridership of a public transport system decreases (Paulley et al., 2006). Public transport schemes with low or near-zero fares have been observed to improve public transit

Table 7
Summary of fare and capacity scenario analyses for the same and varying fare structures across income groups.

Objective function of metro fare setting	Capacity	Fare			Consumer surplus (BDT)	Revenue (BDT)	Total surplus (BDT)	MRT flow			Car flow
		High income	Middle income	Low income				High income	Middle income	Low income	
Same fare											
Maximum consumer surplus (BDT)	57,600	10	10	10	12,395,018	1,939,347	14,334,365	29,115	67,424	97,396	13,424
Maximum revenue (BDT)	57,600	150	150	150	9,465,923	20,473,227	29,939,150	56,521	49,137	30,830	8,017
Maximum total surplus (BDT)	57,600	150	150	150	9,465,923	20,473,227	29,939,150	56,506	49,138	30,844	8,017
Maximum MRT flow											
High income	57,600	150	150	150	9,465,923	20,473,227	29,939,150	56,521	49,137	30,830	8,017
Middle income	57,600	10	10	10	12,395,018	1,939,347	14,334,365	29,115	67,424	97,396	13,424
Low income	57,600	10	10	10	12,395,018	1,939,347	14,334,365	29,115	67,424	97,396	13,424
Minimum car flow	57,600	150	150	150	9,465,923	20,473,227	29,939,150	56,521	49,137	30,830	8,017
Varying fare											
Maximum consumer surplus (BDT)	57,600	10	10	500	19,523,592	1,697,801	21,221,393	62,552	107,228	0	2,738
Maximum revenue (BDT)	57,600	200	150	150	7,451,298	22,043,747	29,495,045	46,807	51,719	32,829	10,139
Maximum total surplus (BDT)	57,600	100	150	150	12,018,140	1,7805,076	29,823,215	62,721	47,328	29,558	6,707
Maximum flow											
High income	57,600	10	500	500	17,289,750	680,812	17,970,562	67,968	2	0	7,519
Middle income	57,600	500	10	500	16,220,879	1,391,890	17,612,769	459	116,230	0	16,804
Low income	57,600	500	500	10	13,361,994	1,514,284	14,876,278	289	1	136,922	24,056
Minimum car flow	57,600	10	10	500	19,523,592	1,697,801	21,221,393	62,552	107,228	0	2,738

ridership and the overall mobility of the low-income population (Cats et al., 2017). However, these demand elasticities are heterogenous in nature and depend on multiple factors such as income, as observed in this study. Paulley et al. (2006) identified the types of relationship that could exist between income and demand for public transport and noted that income affects demand for public transport through car ownership and car trips. They argued that in United Kingdom, the rising average income over the years has resulted in increased car ownership, which has decreased public transport ridership. Developing countries are now witnessing a similar trend whereby car ownership and numbers of car trips have increased continuously (Rahman & Baker, 2018; Verma, 2015). It is well established that car use leads to higher levels of road congestion, environmental pollution, and road accidents. Increasing car ownership in developing countries is therefore a worrying trend. A possible way to encourage people, especially car owners (people who typically belong to the high- or middle-income group in developing countries), to shift to public transport could be to make it more attractive. Controlling the crowding on public transport with higher fares could make these systems more attractive for the car-owning high--income group. In addition, such a fare structure would ensure higher revenues for operators (see Fig. 8). However, this comes at the cost of making these systems less equitable.

Additional scenario analyses with non-uniform pricing, i.e., by varying fares for each income group, were also conducted. Table 7 shows a brief summary of maximum MRT flows, minimum car flow, consumer surplus, revenue, and total surplus across the scenarios for both a similar and a varying fare structure. Similar to the scenarios with uniform pricing, for a variable fare structure, the maximum consumer surplus was also observed with very low fares for the high- and middle-income groups (10 BDT for both) and a very high fare for the low-income group (500 BDT). Naturally, this scenario resulted in zero ridership among low-income commuters and very high ridership among middle- and high-income groups. Meanwhile, maximum revenue was obtained from a scenario where the fares for the high-, middle-, and low-income groups were 200 BDT, 150 BDT, and 150 BDT, respectively. For MRT ridership, maximum flow for the high-income group was observed when their fare was 10 BDT and the fare for the middle- and low-income groups was set at 500 BDT. Meanwhile, maximum flow for the middle- and low-income groups was observed when their fares were very low, 10 BDT for both groups, and the fare for the other income group was highest, i.e., 500 BDT. Minimum car flow was observed in the same scenario that maximized consumer surplus (and a very high combined MRT ridership for the high- and middle-income groups), i.e., when the fares for the high-, middle-, and low-income groups were 10 BDT, 10 BDT, and 500 BDT, respectively. It is neither practical nor ethical to expect the high- and middle-income groups to pay less than the low-income group. However, the trends clearly suggest that car ownership is lower when MRT ridership is high among the high- and middle-income groups. Therefore, a variable fare structure could help maintain a desired level of comfort in the MRT system, for which the high-income group would not mind paying. This could also decrease car use in the same income group. Such a scenario would naturally be less equitable, as the ridership among the low-income group would be lower than the situation where the fare is low for all income groups. However, the additional revenue generated from the high fare could be used to cross-subsidize other public transit systems such as buses. The scenario analysis also included evaluations with zero fare, but those results are not included here. Table 7 shows that the maximum values of consumer surplus, revenue, total surplus, and MRT flows were observed at the highest capacity level, i.e., 57,600 persons per hour (pph). If we assume that cost to the operator in all scenarios is the same, then the sum of consumer surplus and revenue could be compared to gain an idea about the social welfare associated with each scenario. Similar to scenarios with uniform pricing, with non-uniform pricing it may be seen that the scenario with fares of 100 BDT, 150 BDT, and 150 BDT for the high-, middle-, and low-income groups, respectively, produced the highest total surplus, i.e., sum of consumer surplus and revenue. However, this scenario resulted in relatively low levels of MRT ridership for middle- and low-income groups. Therefore, this cannot be deemed an equitable system for all income groups.

The findings of the fare and capacity scenario analysis yielded a mix of intuitive and counterintuitive findings, albeit both important for policymaking. The key takeaways could be summarised as follows: 1) calculation and implementation of optimal fares using a welfare maximization strategy may produce an inequitable system with relatively low ridership for the lower income groups, and 2) ensuring high MRT ridership for lower income groups would result in very low MRT ridership of the car-using high- and middle-income groups and lower revenues for the public transport providers. The findings clearly highlight the trade-off policymakers must make between equity and reducing private vehicle usage. On the one hand, a lower fare could ensure greater ridership by low-income users and would make the MRT system accessible to more people. This could translate into indirect economic growth as higher accessibility would mean better access to economic opportunities. Such an equitable system could revitalize communities, decrease social exclusion, and prove to be an important step towards sustainable development of the city. On the other hand, higher fares would ensure greater comfort in public transport systems. The current analysis clearly shows that this scenario would increase revenue and ridership among the high-income group, of which many are current private vehicle users or could become so in the future. This could translate into lower carbon emissions and reduced congestion on the streets, and as discussed above the revenue generated by the MRT system could be returned to society to improve other public transport systems such as the bus networks, which are currently used by many people in Dhaka. Cross-subsidization across public transport systems could occur whereby the more affluent could contribute for those who are economically and socially disadvantaged. However, the downside to these arguments is that the practical realization is much more difficult than a theoretical proposal. It would require sincere political will, smooth co-ordination among various stakeholders, and a common inclusive vision for the city. Another important point is that the trade-off mentioned above is largely due to the absolute shortage of public transport supply. Increasing the capacity of public transit in addition to MRT line 6 should be a straightforward policy direction to resolve the above-mentioned dilemma. The increased capacity (across different types of public transit systems) then can also cater to the varying sensitivity across different groups. Trains could have a higher number of carriage classes with varying fares which can accommodate all income groups.

For both uniform (i.e., same fares) and non-uniform (i.e., varying fares) fares, only non-zero fares that produce the maximum values for consumer surplus, revenue, and MRT flows are reported.

7. Conclusions

The study had two primary objectives, first, to evaluate the sensitivity of different income groups to crowding on transport systems by analysing their mode choice behaviour. Non-linearity in the effect of crowding on mode choice was factored in by incorporating the crowding variable as a BPR-type function in ML models. Second, to conduct a policy-based scenario analysis to estimate equilibrium passenger flows across different income groups and analyse the influence of fare and capacity settings of the Dhaka metro system on the ridership and social welfare of the users. The objectives were achieved using an SP survey conducted with 361 people living in the Uttara Phase 3 area of Dhaka city making 2,125 SP choices for their mode choice behaviour.

The main findings of this study show that a) the sensitivity to crowding depended on income. It was observed that people in the high-income group were more sensitive to crowding than those in the middle- and low-income groups. The costs of crowding were observed to be greatest for the high-income group, especially at higher levels of crowding. The cost associated with crowding increased nearly exponentially with increased crowding. In addition, b) when this sensitivity to crowding based on income group was accounted for in estimations of demand for the MRT system, it was observed that the demand was heterogenous across groups. The ridership in high-, middle-, and low-income groups depended on the fare. For the high-income group, the demand followed a bell-shaped curve, where the maximum demand was observed for a fare in the range of 150–250 BDT. This indicates that people belonging to the high-income group are willing to pay higher prices for a desired level of comfort. By contrast, for middle- and low-income groups, lower prices (in the range of 0–50 BDT) yielded the highest ridership, indicating that the demand for MRT among people belonging to lower income groups is less sensitive to crowding levels and more sensitive to pricing. The analysis was then extended to calculate the consumer surplus and revenue associated with different scenarios, and it was observed that c) in the case of a similar fare structure across the different income groups, the highest social welfare, i.e., the sum of consumer surplus and revenue, was observed when the fare was 150 BDT, which produced a low demand from the low-income group and relatively high demand from the high-income group. Similarly, d) for a variable pricing scheme with different fares across different income groups, highest social welfare was observed for the scenario whereby the fare for the low- and middle-income groups was in the higher range (150 BDT), resulting in lower MRT ridership among these groups. Meanwhile, e) the lowest levels of car use were observed in the scenario whereby the fare for both the high- and low-income groups was low (10 BDT), so the MRT ridership for these groups was high, indicating a direct correlation between car use and MRT use among these income groups.

The findings highlight the trade-off decision makers would have to make between an equitable public transport system and reducing the use of private vehicles. The findings show that the maximization of social welfare would result in optimal fares that would not be equitable. Lower fares may ensure equity but would drastically reduce supplier benefits. However, relatively higher fares would ensure that high-income people, who are more likely to use private vehicles, would shift to the MRT. The results show that private vehicle use decreases with increased MRT ridership for the high-income group. One of the major contributions of this work is that it provides an empirical basis for the various stakeholders regarding how sensitivity to crowding across different income groups leads to heterogeneities in demand for a public transport system, in this case an MRT system. This evidence would help the stakeholders to make sustainable decisions consistent with the goals and vision of the city. In addition, the study discusses the pros and cons associated with different strategies of fare planning in detail. Finally, it provides important empirical evidence specifically for a case from the developing Global South, where society is rapidly transitioning, and income disparity is stark. Income was observed to be an important influence on travel behaviour decisions and public transport mode choice. Understanding its role and accounting for the heterogeneities across income groups would help in building a sustainable and inclusive system. The approach of this study can be easily adopted and modified for other cities in the world.

This study had several limitations that must be addressed in future studies. First, road congestion was ignored in this study. Actual mode-choice decisions would be heavily affected by the level of congestion on the roads; however, in this study we did not consider it. Future studies must consider the variation in road congestion levels while estimating heterogeneities in demand. Second, the income categories considered in this study may not be truly representative of the population of Dhaka. However, the reason for this is the selection of the study area, which in general houses people who are relatively well off. Studies in the future could conduct a similar analysis with a more representative data of larger sample size. Third, crowding in the existing bus systems was assumed to be constant, whereas in reality the crowding would vary over time and the people's mode choices would naturally be affected by that. Future studies must consider crowding on buses while estimating demand for MRT services. Fourth, many other important variables such as access and egress to stations and crowding on platforms were not considered in the utility formulations. The inclusion of these variables in future would improve estimation accuracy. Fifth, the crowding valuation and the subsequent demand estimation for MRT was conducted based on a SP survey. Revealed preference studies in the past have estimated relatively lower values of crowding cost (Hörcher et al., 2017), indicating possible overestimation in SP survey based estimation. In the current empirical context, it was not possible to collect RP information for MRT in Dhaka but in future after it is operational, such information should be collected and analysed. Sixth, this study did not explicitly model the environmental effects of mode use among the people of Dhaka. It simply assumes private vehicles to be more polluting than public transit. However, there could be variability across different private modes such as the use of less polluting electric vehicles. Similarly, the sensitivity of people towards the different types of private vehicles might vary based on their income. We did not consider these effects in this study. Finally, the study would have benefited hugely from considering operational costs in the discussion on social welfare maximization and equity. In the current context, it was not possible to account for this, but future studies must consider this aspect.

CRediT authorship contribution statement

Varun Varghese: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft. **Md. Moniruzzaman:** Data curation, Software, Validation, Investigation, Formal analysis, Writing – original draft. **Makoto Chikaraishi:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Data availability

The authors do not have permission to share data.

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