Transport Policy 148 (2024) 92–106

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

Developing an agent-based microsimulation for predicting the Bus Rapid Transit (BRT) demand in developing countries: A case study of Dhaka, Bangladesh

Khatun E. Zannat [a,b], Janek Laudan [c], Charisma F. Choudhury [a,*], Stephane Hess [a]

[a] Institute for Transport Studies, University of Leeds, Leeds, LS29JT, UK
[b] Department of Urban and Regional Planning, Chittagong University of Engineering and Technology, Chittagong, 4349, Bangladesh
[c] Institute of Land and Maritime Transport (ILS), Traffic System Planning and Traffic Telematics, Technical University of Berlin, Berlin, Germany

ARTICLE INFO

Keywords:
Bus rapid transit
Agent-based model
MATSim
Public transport
Dhaka
Bangladesh
South Asia

ABSTRACT

Bus Rapid Transit (BRT) has been widely recognised as an affordable and effective mass transport system that can solve various mobility issues in countries that are unable to afford rail-based mass transit options. However, it is extremely challenging to predict the demand for the first BRT service in a city of a developing country with a weak public transport system using aggregate models, given the radical difference in the level of service between the BRT and the existing modes. Further, there can be substantial changes in the activity and travel patterns in a city after the introduction of the BRT which simpler disaggregate level analysis tools are unable to predict. Agent-based simulation tools, which are the state-of-the-art tools for simulating complex travel behaviour, are hence more appropriate for predicting the network conditions after the introduction of a new BRT system. But the application of such simulation tools has been primarily limited to developed countries where the transport landscape and the travel behaviour are very different from the developing countries. To address this gap, this paper presents a demand forecasting model for BRT and integrates it into an activity-based micro-simulation tool in the context of Dhaka, the capital of Bangladesh and one of the fastest growing megacities in the world. The model was developed based on an existing multi-agent, activity-based, travel demand simulator (MATSim). The MATSim implementation in the context of Dhaka focused on two aspects: (1) implementing behaviour models in MATSim to reflect the mode choice in the presence of the proposed BRT (2) integrating multiple data sources (including stated-preference data) for calibrating the mode choice and other components of MATSim to realistically mimic the travel behaviour in the city. Once calibrated, different access scenarios for BRT were simulated using MATSim, and the sensitivity of the outputs to different modelling assumptions is tested. Results from the simulation showed that the marginal utility of travel time, travel cost, and pricing structure of BRT significantly influenced BRT travel demands. Also, BRT demand was found to be the highest (25% of the total trips) in the scenario with multi-modal access/egress connections. While such direct model outputs presented in this paper will be useful for the planners to maximise the ridership of the proposed BRT, the calibrated simulator will be also useful for the evaluation of other innovative transport modes in the context of Dhaka in the future.

1. Introduction

Rapid urbanisation and the associated increase in urban population in developing countries create significant pressure on transportation infrastructure (Makinde et al., 2018), causing various urban mobility challenges such as rising travel demand (Madlener and Sunak, 2011; Melo et al., 2012; Rahman et al., 2012), congestion (Han et al., 2019), safety issues (Cabrera-Arnau et al., 2020), increasing vehicle ownership (Cervero, 1996), and unreliable public transport (PT) services (Poku-Boansi and Marsden, 2018). To address such challenges, the government and policymakers of many countries have sought to prioritise PT in their transport policies (Mavi et al., 2018). In recent years, Bus Rapid Transit (BRT) has been widely recognised as an affordable and effective mass transport system that can solve various mobility issues in countries

* Corresponding author.
E-mail addresses: tskez@leeds.ac.uk (K.E. Zannat), laudan@vsp.tu-berlin.de (J. Laudan), C.F.Choudhury@leeds.ac.uk (C.F. Choudhury), s.hess@leeds.ac.uk (S. Hess).

https://doi.org/10.1016/j.tranpol.2023.12.014
Received 21 March 2023; Received in revised form 6 November 2023; Accepted 21 December 2023
Available online 30 December 2023

which are unable to afford rail-based mass transit options (Joseph et al., 2021; Paget-Seekins, 2015; Schalekamp and Behrens, 2010; Venter et al., 2018).

Although the BRT systems are in operation in many cities, issues related to the planning and implementation of this mode of transport can lead to less successful outcomes (Deng and Nelson, 2013; Poku-Boansi and Marsden, 2018). A lack of knowledge of local settings (e.g., social-spatial system) could limit the success of BRT implementation in attracting people to this mode of transport (Joseph et al., 2021). Achieving a high modal shift to BRT is in fact a challenging process in developing countries due to the increasing income and affordability of private vehicles (e.g., cars and motorcycle) (Satiennam et al., 2016). Besides, predicting the demand for the first BRT service in a city with a weak public transport system proves exceptionally complex, given the radical difference between the BRT and the existing modes. It requires collecting stated preference (SP) data which is rarely done in developing countries (Rastogi, 2000). Further, the spatial transferability performance of the models is typically not good in developing countries (Bwambale et al., 2015, Sanko, 2014). Therefore, to ensure a substantial modal shift and achieve the environmental and mobility benefits resulting from BRT (Cervero, 2013, Hidalgo & Graftieaux, 2008), a city-specific empirical investigation of BRT operation is necessary (Joseph et al., 2021).

The existing studies conducted in the context of developing countries for planning BRT systems primarily adopted classical four-step models. However, the four-step models disregard the constellation of decisions of when, why, and where to travel (Hafezi et al., 2019; Västberg et al., 2020). Predicting the demands of a new transport system such as BRT using simple models is difficult, as the design and operation of BRT are complex, and require a wide range of control measures that are linked to the existing PT services and transportation infrastructure (e.g., rolling stock, right of way, pricing strategy, land use measures) (McCormack et al., 2021; Paget-Seekins, 2015). The agent-based travel demand model has emerged as a new generation of transport modelling and forecasting tools that provides an alternative to the traditional aggregate demand modelling. This modelling approach is flexible, comprehensive, and capable of modelling individual decision-making processes.

Agent based modelling framework (ABM) provides the flexibility to incorporate multiple attributes of agent and their environment in different layer/module formats, and simulate the model to understand urban traffic flows (Grether et al., 2008; Małecki, 2018; Manley et al., 2014), activity behaviours (Arentze et al., 2010; Čertický et al., 2015; Gkiotsalitis and Stathopoulos, 2015; Märki et al., 2014; Shabanpour et al., 2017), changes in land use and effects on environment (Zhang and Zhao, 2018), performance assessment of service (Gao et al., 2016; Ji et al., 2018; Levine et al., 2018), accessibility of location (Huang, 2019), location decision of housing (Ding et al., 2018), joint travel mode and departure time choice (Jing et al., 2018; McDonnell and Zellner, 2011; Zou et al., 2016), joint route choice and departure time choice (Li et al., 2018) and many more. While there have been several attempts to adopt agent-based models for understanding modern complex transport-related issues, those were primarily limited to larger metropolitan planning organisations (MPOs) in developed countries. The application of an agent-based model in fast-growing cities of developing countries poses considerable difficulties due to the required input data (e.g., travel information, census data, and infrastructure-related data), and computational challenges (Kagho et al., 2020).

To address issues regarding travel demand prediction in developing countries, this paper presents a demand forecasting model for BRT and integrates it into an agent-based micro-simulation tool. The model was established in the context of Dhaka, the capital of Bangladesh and one of the fastest-growing megacities in South Asia and the world. An existing multi-agent, activity-based, travel demand simulator (MATSim) has been utilised in this regard. The MATSim implementation in the context of Dhaka focuses on two aspects: (1) implementing behaviour models in MATSim to reflect the mode choice in the presence of the proposed BRT and (2) integrating multiple data sources (including stated-preference data) for calibrating the mode choice and other components of MATSim to realistically mimic the travel behaviour in the city. Finally, the impacts of the two different accessibility scenarios (with and without multimodal feeder service) and two different pricing structures (monthly flat fare and distance-based fare system) were quantified using the calibrated and validated simulator.

The remaining article is organised as follows: first, we provide a short description of the RP and SP data used in this study, followed by a description of the modelling framework. The results from the simulation are then presented with a critical discussion of this study and future research direction.

2. Data

2.1. Study area

This study focused on the Dhaka Metropolitan Region (hereinafter RAJUK area) (Fig. 1). Dhaka, the capital of Bangladesh, is home to more than 15 million people. The population of the city is likely to increase to 26.3 million by 2035, predominantly due to rural-urban migration (DTCA, 2015). To meet the growing mobility demands in this city, the rate of car ownership, as well as the growth of motorised vehicles, have been increasing at an alarming rate. According to the Bangladesh Road Transport Authority (BRTA), 918,233 private motorised vehicles (cars, jeeps, microbuses, and motorcycles) were newly registered in Dhaka between 2011 and 21, while the corresponding number for buses and minibuses was 23,887 (BRTA 2022). Furthermore, there is a particularly inefficient use of road space due to the low occupancy rate of private vehicles. The escalating growth in motorised vehicles, low road capacity, and a lack of traffic management resulted in significant traffic congestion, causing a loss of 3.2 million business hours per day in Dhaka (Siddique et al., 2017). The city's administration does not, however, maintain or organise them efficiently (Sajib, 2021). In Dhaka, public transport service can be characterised by no regular schedule and fixed vehicle stops, overcrowded services, frequent service suspension, and limited traffic service monitoring (Quddus et al., 2019; Rahman, 2022; Satu and Chiu, 2019). The lack of adequate public transportation facilities to fulfil passengers' mobility demands is now a serious concern in this mega city. The World Bank reported that during the morning and evening peak hours, the average vehicle speed is approximately 8.75 km/h in the road network (World Bank, 2015). The mean travel time in peak hours is almost three times higher than the travel time in off-peak hours.

To reduce the level of congestion, the government invested heavily in new infrastructure (e.g., flyovers, BRT, and MRT services) in the last two decades. However, most of the structural interventions have failed to minimise traffic congestion, primarily due to a lack of system-level analyses and the absence of robust transport models (Enam, 2010; Habib, 2002). The Strategic Transport Plan of 2005 (DTCB, 2005) recommended implementing three BRT lines. Among those, line 3 is currently under construction and is expected to be in full operation by the end of 2025. The BRT lines will be operating in parallel to the existing PT services (Fig. 2). The mode choice demand for BRT was estimated only by calibrating PT demand using conventional four-stage modelling while ignoring its potential impact on the existing transport services (e.g., auto-rickshaw, motorcycle, human-hauler), infrastructure, and land use (ADB, 2022).

Considering Dhaka city as a case study area and the under-construction BRT (Line 3 in the Strategic Transport Plan, 2005) as a new transport option, this study focused on developing a simulation environment to assess mode choice behaviour and the impact of BRT in the existing setting. The proposed model aimed to predict the mode choice at an individual scale, over different periods subject to spatial and temporal constraints.

This study utilised both Revealed Preference (RP) and Stated

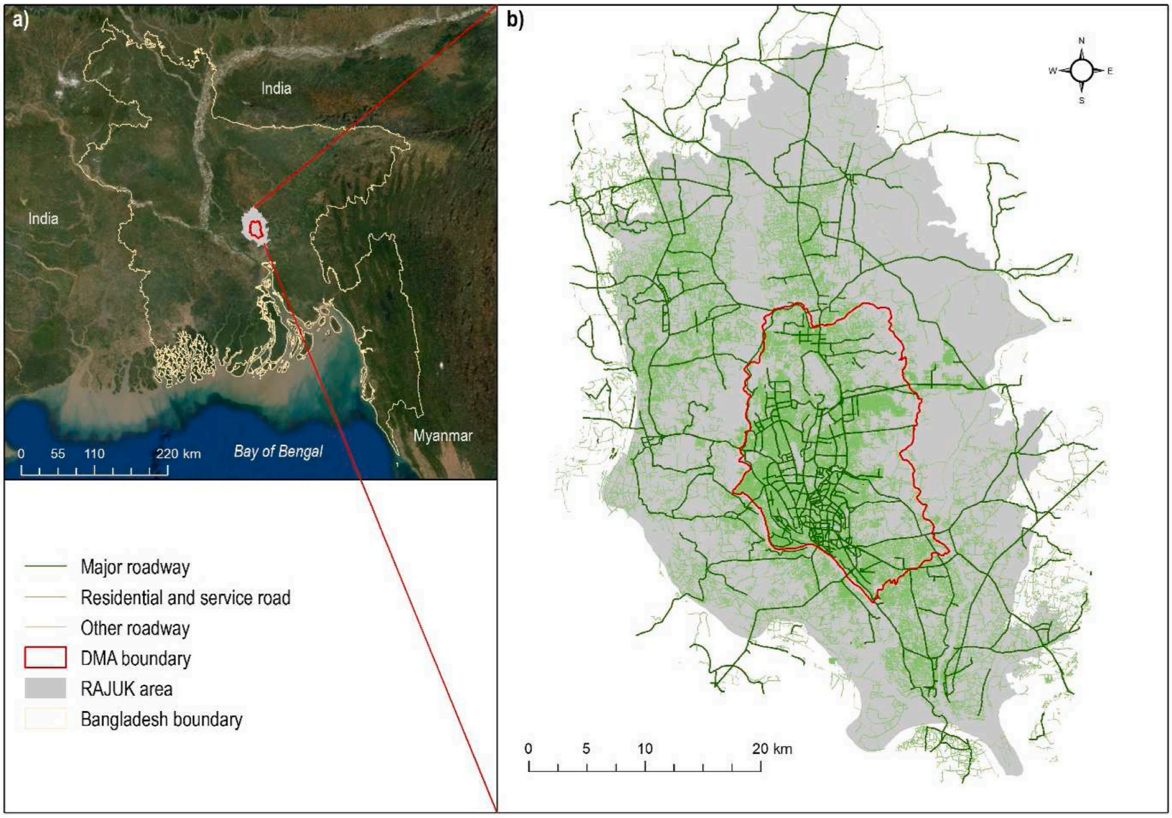

Fig. 1. Location of the study area with the existing road network.

Preference (SP) data for generating the MATSim inputs and development of the mode choice models. The datasets are described below.

2.2. Revealed Preference (RP) data

This study utilised RP data collected from the Dhaka Transport Coordination Authority (DTCA), which commissioned a consulting firm TYPSA (www.typsa.com) to develop the database by carrying out a travel diary survey across the RAJUK area as part of an ongoing Dhaka Subway Project. The survey was conducted from Monday to Saturday between February 28, 2019 to May 4, 2019. The survey form included two main sections. The first part was related to general household characteristics (e.g., age, gender, education, occupation, income, car ownership). The second section included trip-related information (e.g., departure time, travel mode, travel time, trip purpose) of each member of all sample households, who made trips on the previous working day. Information on commuting, education, leisure, personal and other purpose travel was collected. A total of 35,000 households were surveyed in the RAJUK Area, which constitutes approximately 1% of the total households in Dhaka. The details related to the survey, data, and summary can be found in the "Feasibility study and preliminary design for construction of Dhaka subway" report (TYPSA, 2019). The data summary of RP data is presented in Table 1.

2.3. Stated preference (SP) data

Since BRT is an ongoing project, solely the RP data is unable to determine the sensitivity toward attributes (e.g., travel time, travel cost) of this new transport mode. Many studies combined RP and SP data either to analyse the impact or to evaluate the consumer preference for multi-attributed products or services (Ben-Akiva and Morikawa, 1990; Bhat and Castelar, 2002; Brownstone et al., 2000; Rashedi et al., 2017). This is due to the fact that context effects are limited in realistically designed SP choice experiments since SP data are not based on actual market behaviour (Ben-Akiva et al., 1994). Therefore, we also used SP data of 1016 individuals, collected by a roadside questionnaire survey (conducted between December 2009 and January 2010). In the survey, people were presented with hypothetical scenarios - some including BRT and some including Metro Rail (MRT) with different level of service and pictorial representations. They were asked if they would continue the current mode or shift to BRT or MRT in each scenario. Further details on survey design, data collection, and summary findings can be found in Enam (2010). The SP data was used to develop a coupled RP-SP model to understand the preference for BRT and MRT and to improve the accuracy of the parameter estimates. Given the scope of the current work being limited to BRT, only the components of the joint model related to the choice among the existing modes (walk, bike, rickshaw, bus, human hauler, motorcycle, auto-rickshaw) and BRT have been used for the simulation of the future scenarios.

3. MATSim framework

MATSim is an open-source multi-agent traffic simulation platform that consists of several modules, which have been used as a standalone system to implement a large-scale agent-based transport model in several studies (Balmer et al., 2006, 2009; Raney et al., 2003; Vosooghi et al., 2017). This queue-based network simulation platform is the most widely used agent-based simulator in the field of transportation (Balmer et al., 2006; Bouman et al., 2012).

Fig. 3 represents an adaptation of the framework of the MATSim simulator for this study. The simulation sets off with each agent's initial day plan encoded from the daily activity chains of the population of the study area. The virtual world represents the transport infrastructure (road network, service facilities) and land use. Each agent within the simulator can perform their daily activity plan in the corresponding virtual world. With iteration-by-iteration, the initial demand is

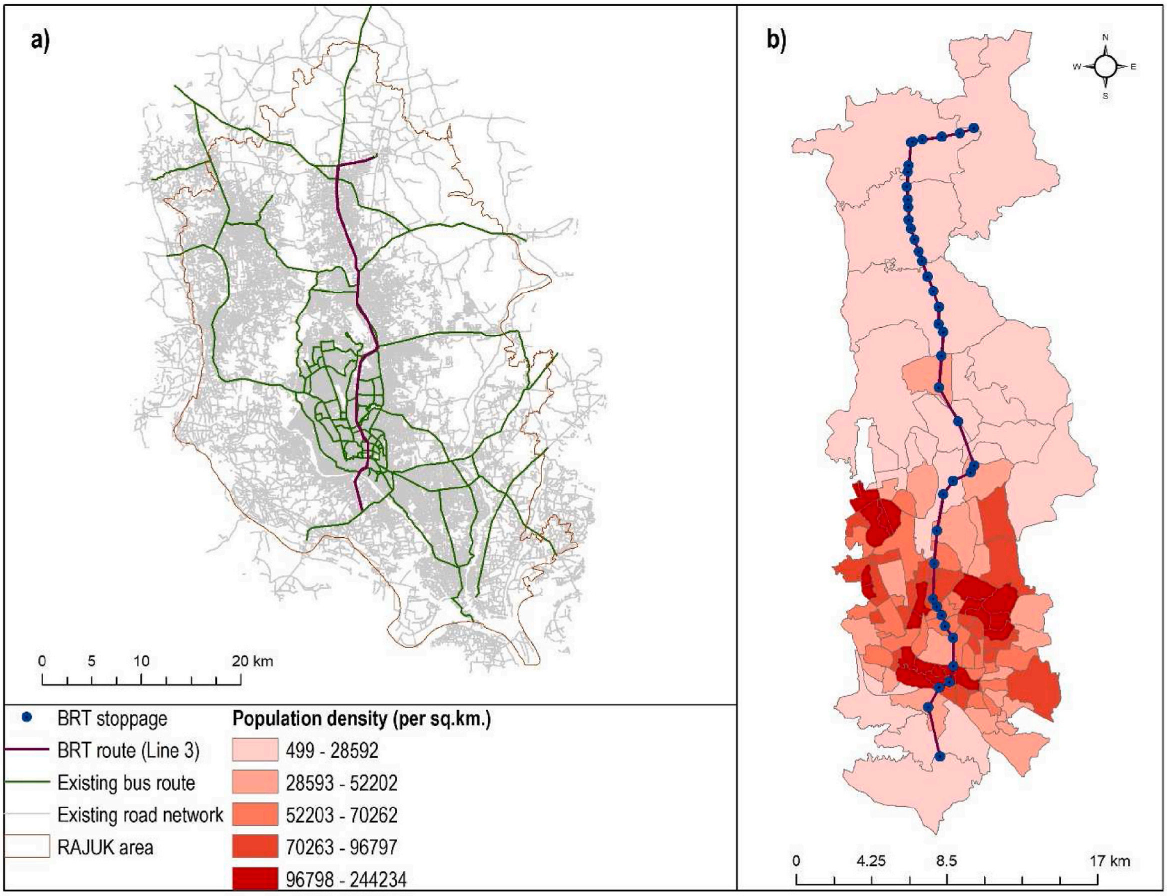

Fig. 2. Population distribution and Transit network.

optimised in mobsim[1] based on its associated score (equivalent to 'the utility function' used in a random utility based econometric framework). This iteration process is repeated until the average score reaches the stable condition. For scoring agents' plans, several parameters can be used for the (dis)utility associated with travelling, waiting, performing an activity, etc. After each iteration, agents' plans are scored to eliminate bad plans (i.e., plans with lower utility) so that only viable day plans can evolve to further iteration steps in the simulation. Further, during the iteration agents are allowed to modify their plan, known as replanning.[2] At this stage, a certain share of agents can change their departure time, route, mode, and location of some activities.

To predict the BRT demand, the overall simulation process was organized into four major steps — simulation inputs preparation, scoring parameter estimation for mode assignment, scoring of agent's activity plan, and running the simulation scenario.

[1] Mobsim is the mobility simulation module in MATSim. Two internal mobsims — QSim and JDEQSim, are available in the MATSim default library. External mobility simulations can also be plugged into MATSim (W Axhausen et al., 2016).

[2] At the replanning stage, each agent can select a strategy for plan selection (best score/logit model/random etc.) and/or an innovation strategy (mode choice, route choice, departure time choice), where a certain plan of an agent is updated. Each strategy is given a weight determining the probability, by which the course of action represented by that strategy is taken. For multiple strategies, weights are normalized. More details about each strategy can be found in Axhausen et al. (2016).

3.1. *Simulation inputs*

MATSIM, in its simplest form, requires three types of inputs: 1) an activity plan of the population of the area (or a representative fraction of the population), 2) a transport network with the description of the road, and 3) configuration (which dictates the specific demand modelling process).

3.1.1. *Activity profile*

Activity demand can be generated either by translating the total population census or by generating a synthetic population using a sample (Axhausen et al., 2016). Since the latest census data available for Dhaka was collected in 2011, we opted for the option to generate activity plans using microdata from a representative sample of the population. The household-level trip diary data from the TYPSA survey (see 2.2 for details) was used in this regard. However, the trip diary only included the detailed geo-location of each participant's household, and the locations of the different activities were only available at the TAZ level. The locations of various activities were randomly assigned within the TAZ boundary using the Geographic Information System (GIS) in a manner that matched the users' stated travel time (Bekhor et al., 2010). After determining location information, an activity profile was generated based on information extracted from travel diary survey data. Each activity plan included information about the activity location (x-y coordinate), end time of the first activity, 'leg' mode, and maximum duration allocated for that activity.

3.1.2. *Infrastructure*

To represent a virtual urban transport landscape of Dhaka, this study utilised a road network and available transport services. The road

Table 1
RP and SP data summary.

Socio-demographic variables	SP (%)	RP (%)
Age		
<18	1.73	12.87
18–25	42.44	17
25–40	42.44	38.48
40–60	12.95	26.68
≥60	0.44	4.97
Gender		
Male	76.41	73.71
Female	23.59	26.29
Household size		
≤5	78.55	88.44
>5	21.45	11.56
Car Ownership		
No car	71.01	93.82
1+ car	28.99	6.18
Occupation		
Student	32.94	24.55
Office-employee	46.33	36.64
Self-employed personnel	12.2	24.31
Housewife	5.72	9.47
Retired	0.65	1.66
Unemployed	1.3	0.75
Other	0.86	2.61
Education		
Below SSC	4.22	36.25
SSC	4.88	15.34
HSC	18.83	19.41
BSC	45.24	13.47
MSC or above	24.89	13.42
Other	1.94	2.11
Income (in BDT)		
<10,000	6.04	1.89
10,000–20,000	15.4	15.16
20,000–30,000	25	24.97
30,000–40,000	16.38	23.47
≥60,000	37.18	34.51

network for the study area was obtained from the Open Street Map (OSM) service. In MATSim, the available modes are car, public transport (PT), bike, and walking. Other modes such as auto-rickshaws and motorcycles, which exist in Dhaka city, are not in-built alternatives in MATSim. They were modelled utilising special *vehicular specifications* within the existing framework in MATSim. These vehicular specifications are presented in Table 2. Since the data represents 1% of the total households in Dhaka City, the supply side adjustment was done in MATSim by considering flow capacity and storage capacity factor of 0.015 (Mehlstäubler, 2019). The outflow capacity of a link — the number of travellers leaving the respective link per time step — is defined by the 'flow capacity'. The number of cars fitting onto a network link per time step (Axhausen et al., 2016) is defined by the 'storage capacity'.

In the latest OSM map, BRT line 3 was not part of the existing road network. Since BRT is an ongoing project, in this study, we developed an artificial network of BRT line 3 and added it to the existing OSM road network. To artificially replicate the BRT operation with the existing network, the following criteria were considered for BRT scheduling and vehicle definition:

- BRT line 3 stations were introduced at the proposed locations.
- BRT route was coded to have a dedicated right-of-way (grade-separated).
- The service frequency of BRT was defined from the standard available in the BRT feasibility report (3-min intervals from 8:00 to 10:00 and 16:00 to 17:00 and 10-min intervals for the remaining time of the day) (ADB, 2022).
- BRT was assumed to be available for all residents of the city.

3.1.3. Configuration

The default configuration settings of the MATSim simulation were used as the starting point in this study. However, in the default module, access/egress mode for PT is only limited to walking. However, in Dhaka, rickshaws are the most widely used access/egress modes. Besides, a considerable number of people use walking and cycling for short-distance trips. Hence, in the multimodal access/egress scenario for

Table 2
Vehicular specification for MATSim implementation.

Mode of transport	Length (meter)	Width (meter)	Maximum velocity (m/s)	PCE
Auto-rickshaw (CNG)	2.7	1	16	1
Motorcycle	2.2	1	22.22	0.5
BRT	18	2.5	25	3

Source: (Kadiyali, 2010), the PCE value of BRT was assumed to be the same as a Tram of similar dimensions

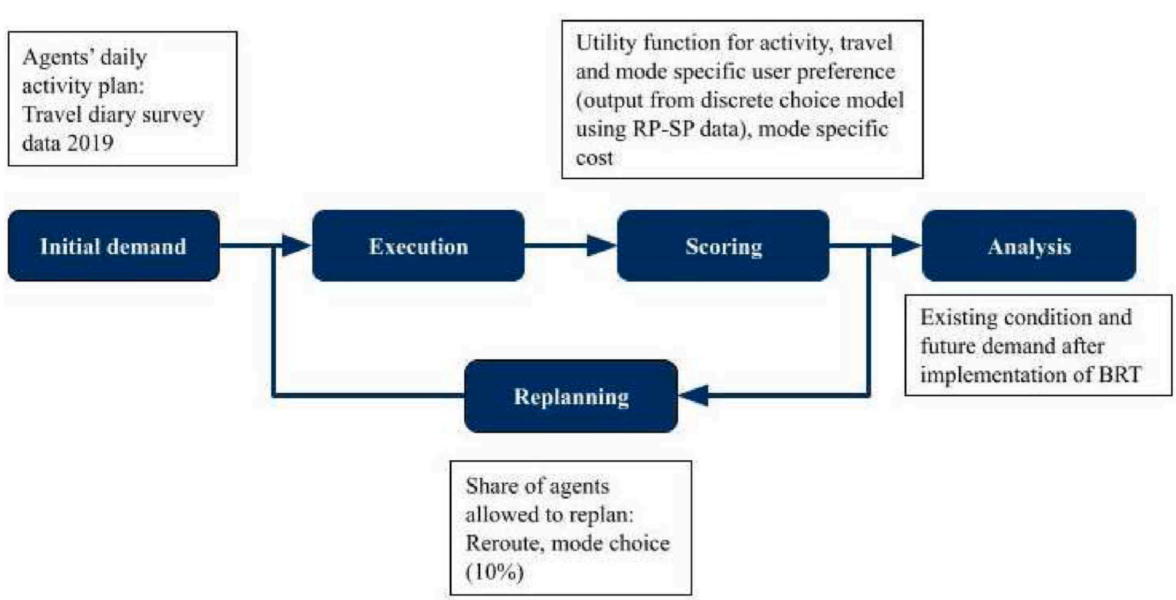

Fig. 3. MATSim simulation framework used in this study.

this study, walking, rickshaw, and bike were considered. Additional search radius parameters were specified for rickshaws and bikes: if no PT stops were found within the initial radius (4 km), the search radius expanded until a stop was found (up to the maximum search radius of 6 km).

3.2. Mode assignment

To estimate the scoring parameters for mode assignment, mode choice models were developed following the random utility framework. The developed mode choice models predicted the choice between existing modes (e.g., car, bus, rickshaw, human hauler, auto-rickshaw, motorcycle, walk, bike) and BRT. The random utility theory suggests that individual decision is followed by rationality and complete information (McFadden, 1973). Agents choose each alternative transport mode with the highest utility, where the utility of an alternative i to a person n has the following form:

$$u_n(i) = u(x_{in}, s_n) \tag{1}$$

where x_{in} is the vector of the attribute of alternative i for individual n and s_n is the vector of characteristics of the person n.

McFadden (1973) proposed that this utility has the linear-in-parameters separable form presented below:

$$u(x_{in}, s_n) = V(x_{in}, s_n) + \varepsilon_{in} \tag{2}$$

where V is the observed component of utility. The unobserved variable ε_{in} represents the random error term. (McFadden, 1973). The choice probabilities for each alternative i in MNL can be expressed as follows (for detail see (Train, 2009)):

$$P_n(i) = \frac{e^{V_{in}}}{\sum_{j \in C_n}^{J} e^{V_{jn}}} \tag{3}$$

C_n is the choice set of individual n. In evaluating the existing scenario, none of the available modes showed correlations in the error term. Therefore, we developed a multinomial logit model to estimate the mode-specific constant and analyse travel time sensitivity, where the error term ε_{in} is independently and identically distributed (IID).

Furthermore, as BRT information was not available in the RP data and using a model-based only on SP data may be prone to hypothetical bias, we developed a joint RP-SP model. As proposed by Ben-Akiva and Morikawa (1990), the difference between the error terms in RP and SP can be modelled as a function of the variances of each type of error and can be presented as follows:

$$\sigma_{RP}^2 = \mu^2 \sigma_{SP}^2 \tag{4}$$

where μ is the scale coefficient.

After adopting the formulation for RP and SP data the utility equation can be written as follows:

$$u^{RP}\left(x_{in}{}^{RP}, s_n\right) = V^{RP}\left(x_{in}{}^{RP}, s_n\right) + \varepsilon_{in}{}^{RP} \tag{5}$$

$$\mu^* u^{SP}\left(x_{in}{}^{SP}, s_n\right) = \mu^*\left(V^{SP}\left(x_{in}{}^{SP}, s_n\right) + \varepsilon_{in}{}^{SP}\right) \tag{6}$$

Probability of choosing alternative i among the available alternative j in the RP data:

$$P_n^{RP}(i) = \frac{e^{V_{in}^{RP}}}{\sum_{j=1}^{J} e^{V_{jn}^{RP}}} \tag{7}$$

Probability of choosing alternative i among the available alternative j in the SP data:

$$P_n^{SP}(i) = \frac{e^{\mu V_{in}^{SP}}}{\sum_{j=1}^{J} e^{\mu V_{jn}^{SP}}} \tag{8}$$

Joint log-likelihood function:

$$LL(\beta) = \left(\sum_{n=1}^{N}\sum_{i} y_{ni}^{RP}\, ln\left(P_{ni}^{RP}\right)\right) * \left(\sum_{n=1}^{N}\sum_{i} y_{ni}^{SP}\, ln\left(P_{ni}^{SP}\right)\right) \tag{9}$$

The coefficients of the joint model were estimated using the maximum likelihood technique using the package Apollo in the R programming language (Hess and Palma, 2019). In the combined model, we used SP and RP specific alternative specific constants. Car travel time for RP data was measured using Google map direction API. Using the same tool, time specific congestion factors were calculated for different origin-destination pairs. Obtained congestion factors and mode specific travel time at free flow speed were used to estimate the travel time of other alternative motorised modes (Bwambale et al., 2019). Travel cost for RP data was measured using distance cost multiplier. We estimated the unknown utility function parameters using the combined model where the common parameter was the travel time and travel cost in our model. Estimates of the common parameters as well as any RP- and SP-specific model parameters were available through joint estimation of the two models. A "scale" parameter was used to equalise the scale of the coefficients of the two models because the variances of the random components of the RP and SP utility functions were likely to differ. The joint model was used for simulating the existing and future mode choice scenarios. The estimated model parameters were used as the scoring parameters (e.g., generic marginal utility of travel time, marginal utility of money) for the simulation. Since using a bike or walking involves kinetic energy rather than a direct monetary cost, we calculated how sensitive walking and cycling are to distance. In order to investigate the effects of the inaugural BRT on different market shares, we also estimated the time sensitivity of different socio-demographic groups (e.g., male vs female, employed vs unemployed, working aged group vs other age group, having a car at the household's vs no car). The model summary used for the simulation is presented in Table 3.

3.3. Scoring of agent's activity plan

In this study, one virtual day was iteratively simulated for a 1% sample of Dhaka city. During the iteration process, a predefined number of agents were allowed to change some of their daily decisions to search for a plan with a higher utility. All agents tried to adapt their plans in such a way that their utility is improved by keeping track of each activity chain. The model was run until the population reached an equilibrium condition (Balmer et al., 2006; Bouman et al., 2012). The plan of each agent at the equilibrium condition was a plausible approximation of the real-world behaviour of an individual.

The optimisation process described above was based on the evaluation of the plans using a specific scoring function. The MATSim scoring function used in this research was formulated by Charypar and Nagel (2005), loosely based on the Vickrey model for road congestion (Vickrey, 1969). The utility of a plan U_{plan} was estimated as the sum of all activity utilities $U_{act,q}$ plus the sum of all travel (dis)utilities $U_{trav,mode(q)}$ as presented below:

$$U_{plan} = \sum_{q=0}^{N-1} U_{act,q} + \sum_{q=0}^{N-1} U_{trav,mode(q)} \tag{13}$$

where N is the number of activities and trip q is the trip that follows activity q.

Following the scoring function, the utility of an activity q is calculated as follows:

$$U_{act,q} = U_{dur,q} + U_{wait,q} + U_{late,q} + U_{early,q} + U_{s.dur,q} \tag{14}$$

Table 3
Discrete choice model.

Parameters	MNL 1			MNL 2		
	Estimate	Robust *t*-stat	Sig.	Estimate	Robust *t*-stat	Sig.
Alternative Specific Constants (ASCs)						
RP specific parameters						
Walking	2.094	35.990	***	2.050	35.608	***
Bike	−0.794	−9.685	***	−0.836	−10.182	***
Rickshaw	1.677	40.000	***	1.648	39.280	***
Bus	2.170	45.400	***	2.128	44.451	***
Human hauler	−0.102	−1.923	**	−0.144	−2.721	***
Motorcycle	0.153	2.967	***	0.113	2.188	***
Auto-rickshaw	0.261	5.872	***	0.212	4.717	***
Car	0	–	–	0	–	–
SP specific parameters						
Rickshaw	−0.439	−1.736	**	−0.762	−2.963	***
Bus	−1.822	−8.468	***	−2.161	−9.929	***
Auto-rickshaw	0.081	0.274		−0.311	−1.091	***
Car	0	–	–	0	–	
BRT	−0.728	−3.786	***	−0.781	−3.891	***
MRT	−1.064	−5.252	***	−1.106	−5.308	***
Level of Service Attributes						
Generic travel time (per hour)	−0.802	−20.753	***			
Generic travel cost (BDT)	−0.002	−7.093	***	−0.003	−8.137	***
Distance sensitivity for walking (m)	−0.125	−15.619	***	−0.128	−16.229	***
Distance sensitivity for cycling (m)	−0.076	−8.834	***	−0.077	−8.941	***
Market specific travel time						
Travel time (base)				−0.309	−5.712	***
Employed				−0.103	−1.729	***
Having car at household				−1.358	−10.670	***
Male				−0.288	−4.709	***
Age between 24 and 40 years old				−0.389	−7.703	***
Scale variables						
mu_RP	1			1		
mu_SP	1.694	3.748	***	1.274	4.355	***
LL(0, whole model)	−209245.3			−209245.3		
LL(final, whole model)	−157093.1			−156657.1		
LL(final RP only model)	−156173.8			−155734.9		
LL(final SP only model)	−919.3			−922.17		
Rho-square (0)	0.2492			0.2513		
Adj.Rho-square (0)	0.2492			0.2512		
AIC	314220			313356.2		
BIC	314382			313556		
Estimated parameters	17			21		

*** Estimates are significant at 95% level of confidence.
** Estimates are significant at 90% level of confidence.
* Estimates are significant at 80% level of confidence.

where $U_{dur,q}$, is the utility of performing activity q, $U_{wait,q}$ denotes waiting time spent in front of the closed activity location, $U_{late,q}$ specifies the late arrival penalty, $U_{early,q}$ defines the penalty for not staying long enough and $U_{s.dur,q}$ is the penalty for a 'too short' activity. This study hypothesised that marginal utility of activity duration will be decreasing logarithmically (the detail will be found in Axhausen et al. (2016)).

The disutility associated with the travel for a leg q is given as:

$$S_{trav,q} = ASC_{mode\ (q)} + \beta_{trav,mode(q)} {}^{*}\, t_{trav,q} + \left(\beta_{distnace,mode(q)} + \beta_{cost,mode(q)} {}^{*} C_{mode\ (q)}\right) d_{trav\ (q)} \tag{15}$$

where $ASC_{mode\ (q)}$ is the mode specific constant, $\beta_{trav,mode(q)}$ is marginal utility of time spent travelling by mode, $t_{trav,q}$ is the travel time between activity locations q and $q+1$. $\beta_{distnace,mode(q)}$ is the marginal utility of distance included in a direct manner for walking and bike use (as these mode requires physical effort). $ASC_{mode\ (q)}$, $\beta_{trav,mode(q)}$, $\beta_{cost,mode(q)}$, and $\beta_{distnace,mode(q)}$ were derived from MNL model (Table 3).

3.4. Other simulation settings

The available modes to the agents at the base scenario were car, bus, rickshaw, human hauler, auto-rickshaw, motorcycle, walk, and bike (Fig. S4 in appendix shows photographs of different transport modes available in the study area). For the future BRT scenario, BRT was added as an additional alternative to the existing modes. The 'real' travel times of car, motorcycle, auto-rickshaw, and BRT were obtained through the traffic simulation component. Due to the exclusion of the narrow roads in the available network files (which are applicable for walking, cycling, and rickshaw), the non-motorised modes were simulated using 'adjusted beeline distances' with the following specifications through the 'teleportation module' within MATSim. Due to the absence of reliable information about the bus and human-hauler routes, they were also simulated using the 'teleportation'[3] feature, but with network-derived travel distances.

For the simulation, two different fare scenarios have been tested: a

[3] Teleportation is a method of moving vehicles from origin to destination, at a predefined speed, without considering interactions in the network.

monthly flat fare and a distance-based cost scenario (cost/km). For the monthly flat fare, the ticket price was assumed to be 900 BDT per month (as it is estimated that about 50% of the commuters spend less than 900 BDT in a month) (ADB, 2022). For the distance-based cost, the distance travelled between activity locations q and $q + 1$ was derived from the activity profiles, and the travel cost per kilometre 1.52 BDT/km was derived from the feasibility report of BRT. All the additional simulation settings are specified in Table 4.

3.5. Simulation scenario

Three different scenarios were simulated for comparison — 1) Base scenario without BRT, 2) Scenario with BRT without multi-modal access, and 3) Scenario with BRT with multimodal access.

A summary of various scenarios used to simulate traffic is presented in Table 5.

4. Results

4.1. Scenario 1: base scenario

The base scenario of the proposed mode choice model reflects the existing conditions (pre-BRT scenario) of modal share, trip purpose, and departure time choice. In this scenario, agents were allowed to change the route to obtain the shortest path. To start with a more stable base model, we also allowed our agents to change one single trip mode (randomly picked) till agents reached their equilibrium. We compared the simulated modal share and departure time choice with the observed data obtained from the travel diary survey conducted in 2019. For the validation, the simulated modal share was also compared with the modal share of the passenger trips collected using an inner cordon line survey, in 2014 by the JICA study team. The results indicated that public transport and non-motorised transport constituted the highest share of trips in Dhaka City. As Table 6 exhibits, the simulated proportion of modal share had a good agreement with the observed and JICA data. However, a difference between the observed and simulated proportion of the modal share of the agents was discernible for existing NMT and Auto-rickshaw, which is approximately 19% and 10%, respectively. We accepted these differences due to the validation of these differences in the external sources. Also, it should be worth mentioning the fact that rickshaws and bikes are not legally permitted along the major roads in Dhaka. We attempted to restrict those vehicles along the major road while routing without network simulation. However, due to a lack of law enforcement, people can use those prohibited vehicles along the major road while violating the law.

The base model also showed the agents' choice of departure time and trip purpose in existing situation. During a weekday, for both home-based outbound and return trips, the number of mandatory trips (i.e., work and education) (more than 80% trips) was the highest in Dhaka city. However, the proportion of trips for personal reasons, leisure activities, shopping, and other purposes was substantially low during the weekday. In comparison to home-based travels, the proportion of non-home-based trips was extremely small, accounting for less than 5% of all observed trips. In the case of departure time choice, most of the agents started their trips before 9:00 for work and educational purposes. However, departure times for other activities peaked at 10:00. (Fig. 4).

Table 4
Simulation settings.

Mode	Speed	Distance	Cost
Bus	16 km/h	Network-derived	1.52 BDT/km
Rickshaw	10 km/h	2* bee-line distance	10 BDT/km
Human-hauler	13 km/h	Network-derived	2 BDT/km
Auto-rickshaw	Network derived	Network-derived	8 BDT/km
Car	Network derived	Network-derived	6 BDT/km
Motorcycle	Network derived	Network-derived	6 BDT/km
Walk	3 km/h	1.4* bee-line distance	
Bike	8 km/h	1.3* bee-line distance	

Table 5
Summary of different scenarios.

	Scenarios	Input	Scoring
1	Base scenario (without BRT)	- Existing road network of Dhaka city - One day activity profile - Configuration	MNL 1 model
2	Future scenario with BRT	- Existing road network of Dhaka city with BRT line 3 and stoppages - One day activity profile - Configuration without multimodal accessibility	MNL 1 model MNL 2 model (for different market share)
3	Future scenario with BRT	- Existing road network of Dhaka city with BRT line 3 and stoppages - One day activity profile - Configuration with multimodal accessibility	MNL 1 model MNL 2 model (for different market share)

Table 6
Observed vs simulated modal share.

	Observed passenger modal share (%)	Simulated passenger modal share (%)	JICA survey (2014) passenger modal share (%)
Bus and Human-hauler	49.2	53.0	68.4
NMT (walking/ rickshaw/ bike)	34.8	16.0	13.4
Car	3.7	11.0	8.2
Auto-rickshaw	7.0	17.0	8.4
Motorcycle	5.3	3.0	1.6

The distribution of simulated travel time was further compared against the user-stated travel time. Fig. 5 shows that in both the observation and simulation, the majority of agents' travel duration ranges from 20 to 40 minutes. Such a validation process yielded a very good agreement between the observed and modelled travel time distributions (Fig. 5).

4.2. Future mode choice scenarios

This study analysed sensitivity to travel time, travel cost, and multimodal access-egress modes in post-BRT implementation scenarios. Each of these three variables was included in the model stepwise.

4.2.1. Scenario 2: future scenario with BRT and without multi-modal accessibility

In scenario 2, we intended to see how travel time and travel cost will influence agents' mode choice behaviour after the implementation of BRT. Here, to avail of BRT, agents could only use walking as an access/egress mode. We tested the influence of travel time independently, as well as in combination with travel cost as a function of distance. For scoring in the simulation, the mode choice model provided the marginal utility of travel time and travel cost and distance disutility for a mode which required physical effort of the agent (e.g., walking and biking).

The optimisation results of travel time showed that if all else being equal, agents chose the mode of transport that yielded the minimum travel time. In this case, motorcycle resulted in the highest modal share (approximately 65%) at the equilibrium point (scenario 2A, Fig. 6 (a)). Since, results from the discrete choice model highlighted the significance of both time and cost sensitivity in predicting agents' mode choice preference, in this study, we also investigated the trade-off between travel time and travel cost. Results showed that agents chose the mode of

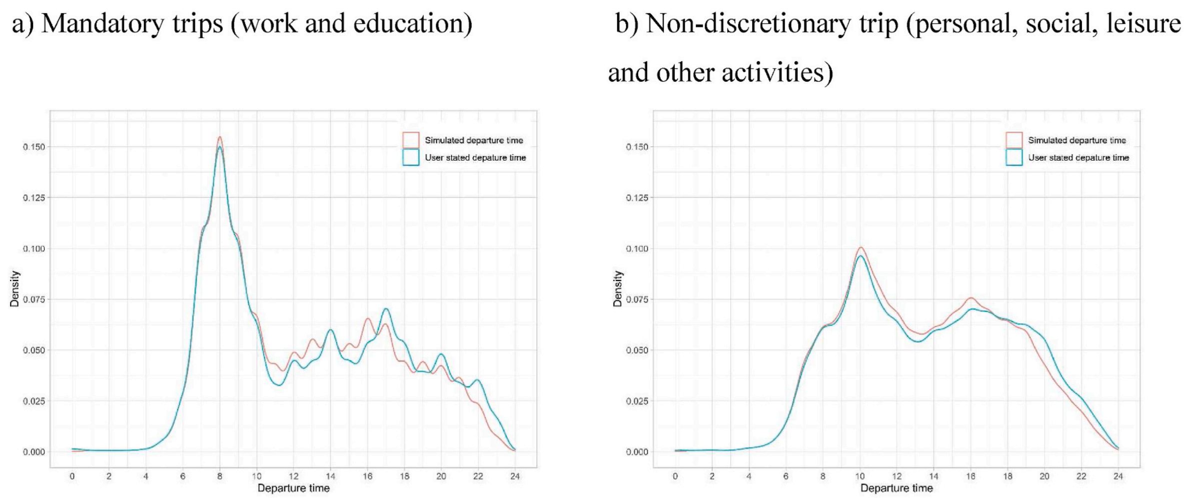

Fig. 4. Observed vs Simulated departure time density at the base scenario for different trip purposes.

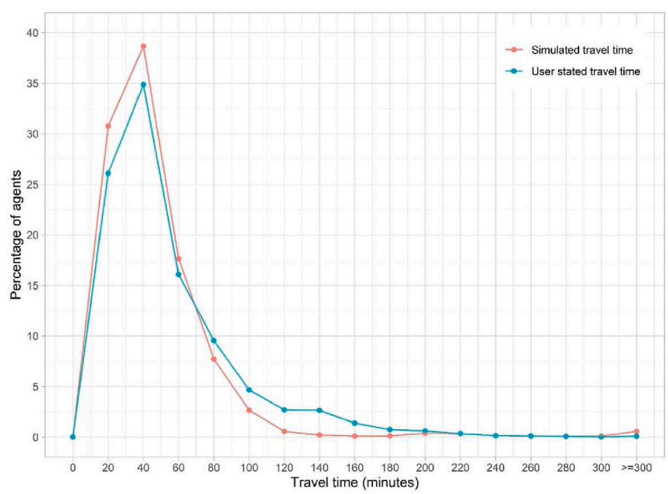

Fig. 5. Comparsion of travel time in simulation and user stated travel time.

transport that required the least travel cost and travel time. The highest modal share was obtained in the bus at the equilibrium point (Fig. 7 (a) and Supplementary Fig. S1). The implementation of BRT with walk as an access mode would attract 1.2% of the total users from other modes, particularly buses, rickshaws, and motorcycles (scenario 2B). A decrease in the link flow of network simulated motorised modes (car, motorcycle, and auto-rickshaw) was noticeable along the road parallel to the BRT network (Dhaka-Mymensingh highway) at various times of the day, however, there was also an increase in link flow at various times in different links (Supplementary Fig. S3).

From the simulation of this scenario, it can be found that a significant proportion of trips (64.2%) could still take place on buses, followed by auto-rickshaws (15.2%) (Fig. 7 (b)). The average travel distance of BRT users would be 10 km (sd ± 6.9 km). We have also examined the impact of a BRT service's flat monthly fare on demand (scenario 2C). The demand for BRT would marginally increase to 1.4% with this fare structure. The simulation result, however, indicated a considerable increase in the average journey distance of potential BRT users (11 km, sd ± 7.8 km). On the contrary, in the distance-based cost simulation, agents would avail each BRT stoppage on an average by walking approximately 650m (sd ± 500m), whereas, for the flat fare cost simulation agents avail each stoppage by travelling 550m (sd ± 420m).

When the simulation considered travel cost as a function of distance, the proportions of home-based and non-home-based trips of the potential BRT users were 91.5% and 8.5%, respectively (scenario 2B). Among the home-based trips, 65.3% were work-related. In this case, non-home-based work trips were 77.9% (Supplementary Table S1). Similarly, at the simulation of the monthly flat fare of BRT service, about 67.5% of trips were home-based work trips, while 80.0% were non-home-based

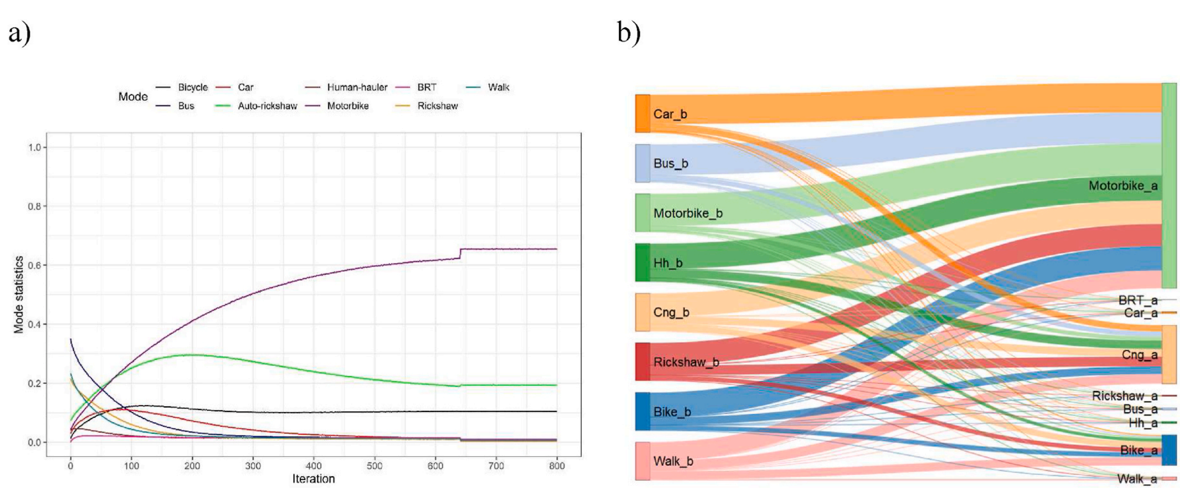

Fig. 6. a) Optimisation of travel time across various modes; b) modal shift based on travel time preference.

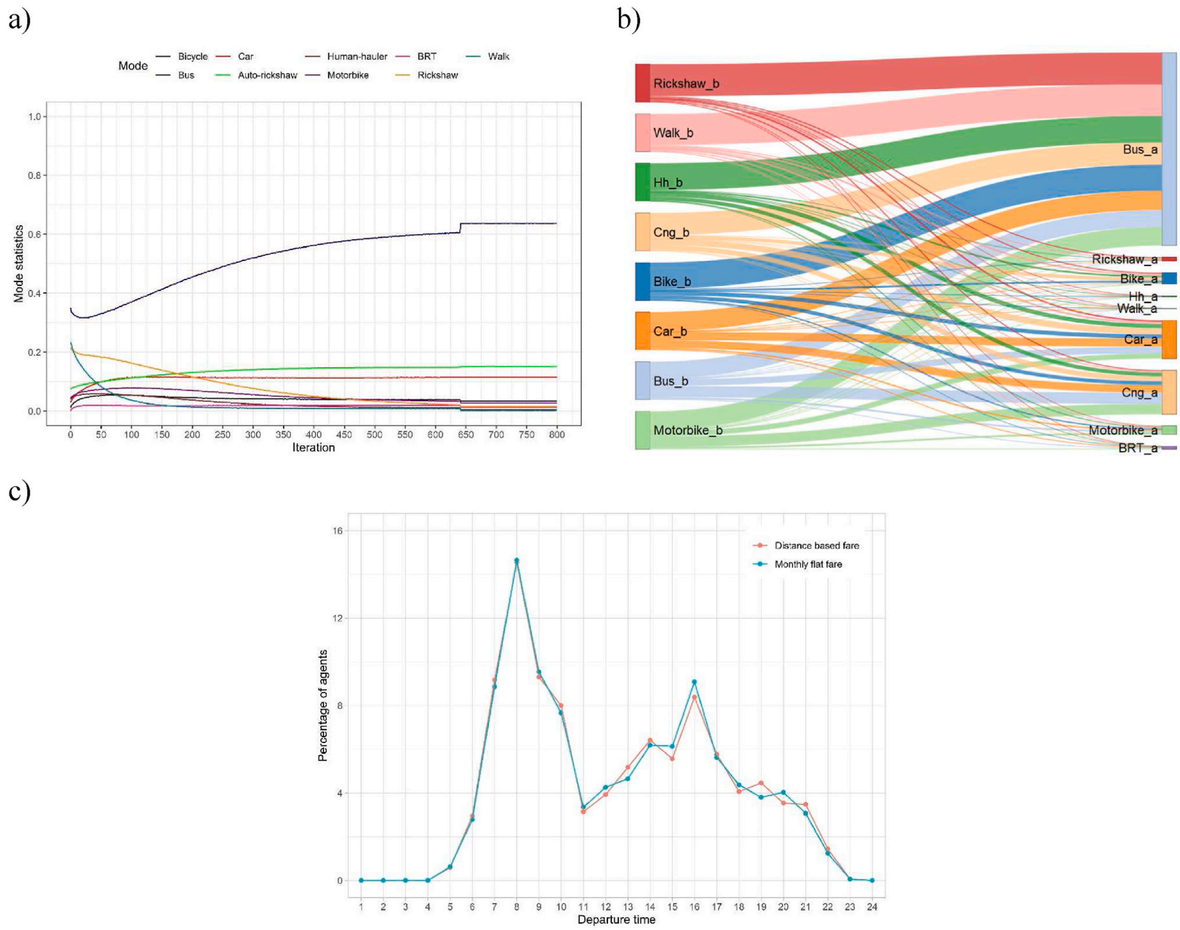

Fig. 7. a) Optimisation of travel time and travel cost (function of distance) across various modes; b) modal shift based on travel cost (function of distance) preference; c) Departure time choice of potential BRT users under different pricing structure of BRT.

work trips (scenario 2C). In both cost scenarios, the BRT users would prefer to depart either during the morning (7:00–9:00) or afternoon (16:00–18:00) (Fig. 7 (c)). Considering departure time, multiple peaks were observed in a working day (Fig. 7 (c)).

In this study, we also simulated the potential demand for BRT while taking into account the varying temporal sensitivity of various market shares. According to the simulation results, the potential demand for BRT varies between 0.6% and 0.7% for different market shares. The majority of potential BRT users would be those who were younger than 25 or older than 40 (40% of 0.6% were aged between 25 and 40 years old), employed (73.5% of 0.7% BRT users were employed), male (80.3% of 0.7% BRT users were male), and did not have a private car in the household (91.7% of 0.6% BRT users did not have a car) (Supplementary Table S3).

4.2.2. *Scenario 3: future scenario with BRT and multi-modal accessibility*

The third scenario considered the travel time and travel cost of users, as well as the presence of multimodal access-egress modes. The

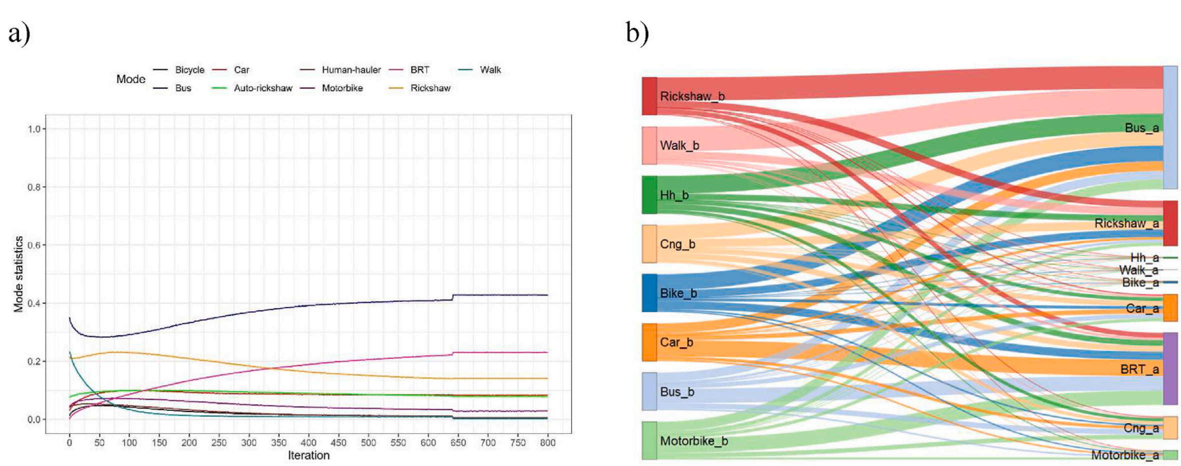

Fig. 8. a) Distribution of modal share at multi-modal accessibility scenario; b) modal shift based on the presence of multimodal access-egress modes.

distribution of modal share at equilibrium points (Fig. 8 and Supplementary Fig. S2) under this scenario indicated that users would still use the bus as their preferred mode of transport. The implementation of BRT with multimodal accessibility could attract approximately 23% of the total users from other modes (e.g., bus, rickshaws, and motorcycles) in both fare systems. This scenario also noted a significant reduction in the link flow along the existing road parallel to the BRT line (Supplementary Fig. S3). In this scenario (3A), about 60.5% of the total potential BRT users would be the existing bus users (Fig. 8 (b)), followed by rickshaws (11.8%) and motorcycles (7.3%). The approximately similar result was obtained from the simulation of a monthly flat fare system with multimodal transport accessibility (Supplementary Fig. S2).

In both fare systems with multi-modal transport accessibility, the proportion of home-based trips was approximately 93% whereas the highest proportion of BRT trips were work (63%) and education (21%) related (Supplementary Table S1). Among the non-home-based trips, the majority of the trips were work related trips (73%) which was followed by personal activities (15%), and shopping (5%). It is noteworthy that the BRT users could travel approximately 12 km (sd ± 6 km), on average, in different fare systems. In both fare systems, most of them would prefer to depart between 7:00 to 10:00 (Supplementary Table S2). Furthermore, the proportions of the walk, bike, and rickshaw usage, as access modes, for any of the trip legs of BRT users, were found to be 1.3%, 7.6%, and 91.1%, respectively. In different multi-modal simulation scenarios, agents were availing of BRT service by travelling approximately 1.7 km (sd ± 1.3 km) using different non-motorised transport allowed as access/egress mode. While considering the different travel time sensitivity of different market share in the multimodal accessibility scenario, BRT service would attract approximately 24–25% of the total users from other modes. Like scenario 2, among these potential BRT users majority of them were employed, younger than 25 or older than 40, male, and did not have a private car in the household (Supplementary Table S3).

5. Discussion of results and policy implications

Transportation demand prediction is essential to evaluate the investment in future transport infrastructure. This is particularly important for a mega project like BRT since investment in such a project has both success and failure records in history. Agent-based microsimulation approach has received wider attention recently, to forecast travel behaviour (Makinde et al., 2018). While the application of this approach in evaluating transport service/infrastructure is common in developed countries (Manser et al., 2020; Moreno et al., 2018), there is a lack of attempt to adopt such a method in developing countries, potentially limiting the effectiveness of new transport infrastructure and service (Yagi and Mohammadian, 2010). This research gap led to this study where we developed an agent-based model to predict future travel demands of an ongoing Bus Rapid Transit (BRT) project in Dhaka city of Bangladesh.

In this study, a base scenario was developed to artificially represent the existing travel pattern in Dhaka city, combining an estimated discrete choice model with a MATSim interface that combines the demand and supply sides. Results from the base model showed that public transport services (bus, human-hauler) and non-motorised transport (walking and rickshaw) constituted the highest share of trips. This simulated result complied with the observation and survey results from the most recently available cordon line survey data collected by the JICA study team (DTCA, 2015).

The calibrated agent-based-microsimulation tool was then applied to simulate and compare the future travel demand of BRT in three scenarios: (1) existing scenario, (2) future scenario with BRT and without multimodal accessibility, and (3) future scenario with BRT and with multimodal accessibility. The results indicated that agents, sensitive to travel time, chose the quickest mode for their daily trips. After the implementation of BRT line 3, the share of trips by motorcycle increased by 65% when agents were only time-sensitive (scenario 2A). In Dhaka city, the number of yearly registered motorcycles increased from 34,707 in 2011 to 99,810 in 2021 (BRTA, 2022), primarily due to its flexible route, door-to-door access, and relatively lower travel time than other alternatives (Wadud, 2020). Besides, the expected total journey time by BRT was greater than the motorcycles, despite the higher average travel speed of BRT as a journey by BRT involved access and egress time (Mavi et al., 2018; Shi et al., 2021; Zgheib et al., 2020) making it less attractive than motorcycles which can provide seamless door-to-door trip. *Therefore, in order to shift people to BRT, the transport policy should include measures to make motorcycles less attractive — by increasing the import duties of motorcycles or by restricting them on the routes competing with BRT for instance.* Given that motorcycles currently have significant detrimental effects on air quality (Chiou et al., 2009) and road safety (Wadud, 2020), such policies can have a significant contribution to improving transport sustainability.

The simulation results further showed that after the implementation of BRT, a substantial proportion of passenger trips would still be based on buses when agents are both travel time and travel cost sensitive (scenario 2B and scenario 2C). While BRT intends to optimise both travel time and travel cost, this study only considered BRT line 3, which connects the north and south parts of Dhaka. Hence, dwellers in the rest of the city area would still be partially dependent on the existing PT services to fulfil their mobility demands. Therefore, to increase the PT ridership, revitalising the existing PT and enhancing inter-modal connectivity with BRT are imperative along with the construction of new BRT lines (Duarte and Rojas, 2012). The importance of intermodal connectivity is also supported by the result from scenario 3. The outputs of scenario 3 indicated that the presence of rickshaws or bikes as access/egress modes would substantially increase BRT service areas (from 0.7% to 25%), increasing the number of long-distance trips (Fig. 9 shows the potential trip distribution of BRT users). These findings may have two important policy implications*: 1) There is a strong likelihood that BRT would be appealing to city dwellers as an efficient and effective mode of public transportation to meet the current passenger travel demand if BRT has an efficient and reliable operation, intermodal connectivity, and service frequency. The efficient operation may reduce the demand for other motorised mode of transport (Supplementary Fig. S3). It may increase travel demand along the access/egress connection street to accommodate first and last mile trips, potentially shifting congestion from major streets to the connecting streets. BRT demand could decrease to 0.7% if link street is unable to meet the anticipated access/egress demand.* The significance of connection and level of service features in meeting passenger transport demand by BRT was also highlighted in the empirical research by Joseph et al. (2021). Additionally, it was noticed from the simulation of scenario 2 that there was a possibility of an increase in link flow along the parallel road of the BRT network at various times of the day (Supplementary Fig. S3). This is because switching to BRT would relieve traffic on the parallel road, which might then make it the quickest path for passengers travelling between other origin-destinations. A further increase in link flow may result in jam density instead of relieving congestion.

This study also found the sensitivity of the fare structure on the BRT travel demands. Though consideration of walking as an access mode with a monthly flat fare of BRT had induced a slight increase in BRT demand (1.2%–1.4%), however, significance of different fare structures was discernible while evaluating the average journey distances of BRT users. This is because monthly flat fares induced more long-distance trips (average journey distance increased from 10 km to 11 km with sd ± 7.8 km). Similarly, the result showed that multi-modal accessibility further increased the average journey distance (scenario 3). *Therefore, the availability of different fare schemes would be effective in increasing BRT ridership (particularly long-distance traveller) and reducing congestion along the busy corridor.* It may be noted that Yagi and Mohammadian (2008) also highlighted the significance of different fare scheme in increasing BRT ridership in Jakarta, Indonesia, using an opinion survey.

In terms of trip purposes, home-based work trips during the

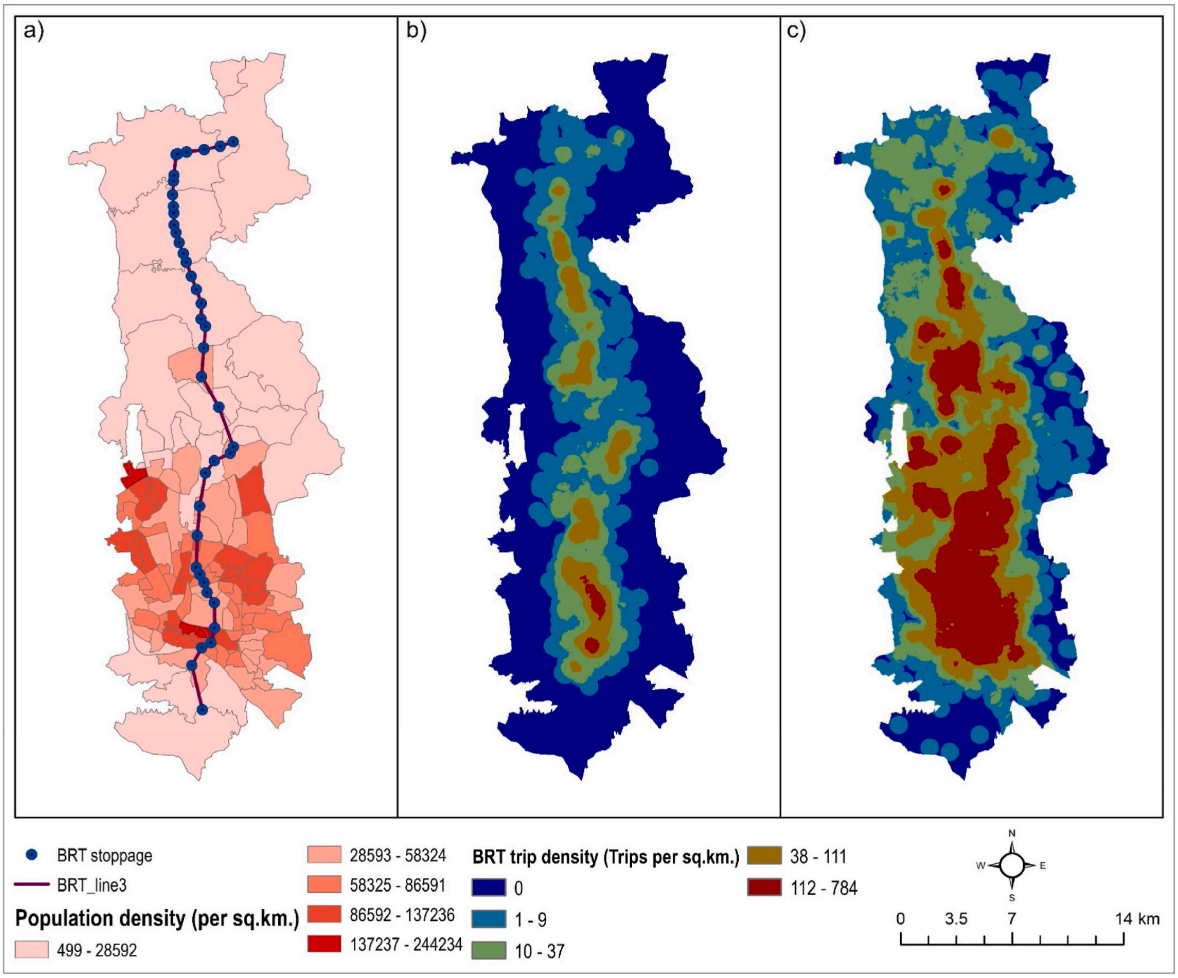

Fig. 9. Potential BRT users' trip distribution pattern (a) BRT network, b) trip density without multi-modal connectivity, c) trip density with multi-modal connectivity).

weekdays would constitute the majority of the BRT trips. This indicates the need for taking special policy interventions to make BRT similarly attractive for discretionary trips. *Potential measures may include an introduction of group tickets, integrated fare systems, and periodical (weekly or monthly passes) and multi-trip tickets could encourage people to use BRT* (Currie and Delbosc, 2013, 2014). Furthermore, results from this study highlighted that demand for BRT would vary across different socio-demographic groups due to their different sensitivity to different levels of service attributes. For example: due to different time sensitivity the demand for BRT would be dominated by the employment status, gender, and car ownership at the household level. *Therefore, BRT ridership enhancement policies should include customised services* (e.g., *commuters' trip tickets, workplace incentives) or targeted marketing approaches* (e.g., *gender-sensitive planning), to better align with the preferences and sensitivities of distinct socio-demographic groups.*

6. Conclusion

This study predicted the BRT demand of Dhaka city, using an agent-based micro-simulation approach. A mode choice model was developed using both RP and SP data which was implemented in MATSim. The developed models worked reasonably well among all the dimensions (travel time, travel cost and access/egress mode) considered in this study. In terms of practical application, the model developed in this study may help to understand the activity patterns and travel behaviour of the traveller after the initiation of a new BRT service. The Strategic Transport Plan (STP) (2005–2025) and DTCA (2015) predicted that the expected modal share of BRT in Dhaka city would be 3% for the proposed three BRT lines (Ahmed et al., 2018). But the predicted BRT demand in this study ranged between 0.7% and 25% while taking into account the marginal utility of travel time, various combinations of fare structures, and multi-modal access/egress connection. In the STP, only public transport simulation was conducted, considering walking as an access mode. Such a demand prediction model ignored the potential shifts from other modes (e.g., rickshaw, motorcycle, human hauler), which have been considered in this study. The findings of this study are expected to provide more reliable results. The key ridership enhancement policies inferred from the findings of this study are listed below:

1. Successful implementation of large mega-projects like BRT should consider the competitive advantages of other transportation modes, motorcycles in particular. Policy measures to make motorcycles less attractive, by increasing the import duties of motorcycles or by restricting them on the routes competing with BRT for instance, are hence crucial for shifting people to BRT.
2. Integration with current transportation services and intermodal connectivity is a prerequisite for increasing the BRT system. In particular, taking policy measures to promote the use of rickshaws and bikes as access/egress modes will substantially increase BRT service areas and help to increase the number of long-distance trips. It is crucial to take measures to ensure the link streets to the BRT line are capable of meeting the access/egress demand of the feeder modes (rickshaws and bikes).

3. Given the heterogeneous sensitivity to the level-of-service variables, policies aimed at increasing BRT ridership should incorporate tailored services (like workplace incentives and commuter trip tickets) and focused planning and marketing strategies (like gender-sensitive planning and promotion). These will ensure that BRT is able to better cater to the sensitivities of various socio-demographic groups and improve ridership.

Future research directions

While the direct model outputs presented in this paper will be useful for the planners to maximise the ridership of the proposed BRT, the calibrated simulator will be useful for evaluating strategies related to BRT ridership and innovative transport modes in the context of Dhaka. Some of the potential future research directions are outlined here:

The agent-based multimodal simulation only tested a limited number of level-of-service attributes (e.g., fare values already proposed by the consultants, no consideration for special fare types to attract discretionary travel, integrated ticket system with regular PT, etc.). Testing wider ranges of values and different combinations of level of service attributes can help to identify further strategies for improving BRT ridership. Also, other choice behaviour such as departure time choice and destination choice behaviour would be worthwhile to explore because ignoring the full range of behavioural changes may lead to over/underestimation of the potential benefits of the mega project.

Once the BRT is operational, it will potentially change the current interaction pattern of different types of travellers (such as new transit users, conventional transit users, users of other modes of transportation) and service providers, law enforcement authorities, policymakers, etc. involved in the existing system (Joseph et al., 2021; Palacios et al., 2020). Due to the chaining and feedback effect, such interactions between agents and the transport system can have an impact on other system components (such as land use, economic conditions, etc.) while agents will be making decisions about their daily activities and mobility (e.g., what activity, when, where, what mode of transport) (Venter et al., 2018; Zgheib et al., 2020). In parallel, it will change the landscape of the city by enhancing connectivity, sprawling, gentrification, densification, land use change, and many more. Such a feedback loop might result in nonlinear causality within the adapted or evolved system bringing radical change in how agents act and how travellers behave (Ettema et al., 2014). Therefore, in future research, our current model can be elevated to a more dynamic model by incorporating the emerging interaction of individual agents with other agents and the environment.

It is expected that after the implementation of policy intervention (e.g., BRT, MRT, expressway, etc.), the current or preferred choice will be also affected by their habits, awareness, evolving attitude, culture, social norms and values (Shafi et al., 2022; Wee and Kroesen, 2022; Zmud and Sener, 2017). If a new BRT line is introduced and users find the service to be convenient and easy to use, this may transform their perception of public transportation and encourage them to utilise the service more regularly (Ramos et al., 2019). Similarly, adaptation to this new service may change their current social belief and perspective (Forward, 2019). However, it is extremely challenging to capture detailed behavioural nuances like exploration, habit formation, inertia, etc. using stated preference data. Extending the current model to capture these behavioural nuances using revealed data collected after opening of the BRT will be an interesting direction for future research. Such a model will also be useful for ex-post evaluation of the BRT system.

However, the way MATSim was adapted for use in the multi-modal context of a developing country is likely to be useful for other countries interested in transitioning to transport policy evaluations using agent-based microsimulation. It may be noted that the developed model is available as open-source software for ease of application in other cities and countries.

Author contribution

The authors confirm contribution to the paper as follows: study conception and design: KZ; data collection: KZ, CC; analysis and software: KZ, JL; interpretation of results and model refinement: KZ, JL, CC &; SH; manuscript preparation: KZ. All authors reviewed the results and the responses and approved the final version of the manuscript.

KZ: Conceptualization, Methodology, Data collection, Software, Formal analysis, Writing - Original Draft, Writing - Review & Editing.

CFC: Methodology, Data collection, Writing - Review & Editing, Supervision.

JL: Software, Writing - Review & Editing.

SH: Writing - Review & Editing, Supervision.

Data availability

The authors do not have permission to share data.

Acknowledgement

This research is funded by the Faculty for the Future Program of the Schlumberger Foundation. Charisma Choudhury's time has been partially supported by the UKRI Future Leader Fellowship [MR/T020423/1]. The data used for the study has been made available by the Dhaka Transport Coordination Agency (DTCA). We also acknowledge the support from Mr Anisur Rahman and Mr Dhrubo Alam of DTCA for providing clarifications regarding the data. We acknowledge the training and logistic support from the Technical University of Berlin, Germany. Also, this simulation work was undertaken on ARC4, part of the High-Performance Computing facilities at the University of Leeds, UK.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tranpol.2023.12.014.

References

ADB, 2022. Preparing the greater Dhaka sustainable urban transport corridor. Asian Development Bank (ADB).Final report, Dhaka, Bangladesh.
Ahmed, S., Nahiduzzaman, K.M., Hasan, M.M.U., 2018. Dhaka, Bangladesh: Unpacking challenges and reflecting on unjust transitions. Cities 77, 142–157.
Arentze, T.A., Ettema, D., Timmermans, H.J., 2010. Incorporating time and income constraints in dynamic agent-based models of activity generation and time use: approach and illustration. Transport. Res. C Emerg. Technol. 18, 71–83.
Axhausen, K.W., Horni, A., Nagel, K., 2016. The Multi-Agent Transport Simulation MATSim. Ubiquity Press.
Balmer, M., Axhausen, K.W., Nagel, K., 2006. Agent-based demand-modeling framework for large-scale microsimulations. Transport. Res. Rec. 1985, 125–134.
Balmer, M., Rieser, M., Meister, K., Charypar, D., Lefebvre, N., Nagel, K., 2009. MATSim-T: architecture and simulation times. *Multi-agent systems for traffic and transportation engineering*. IGI Global 57–78.
Bekhor, S., Dobler, C., Axhausen, K.W., 2010. Integration of activity-based with agent-based models: an example from the tel aviv model and MATSim. Arbeitsberichte Verkehrs-und Raumplanung 628.
Ben-Akiva, M., Morikawa, T., 1990. Estimation of switching models from revealed preferences and stated intentions. Transport. Res. Gen. 24, 485–495.
Ben-Akiva, M., Bradley, M., Morikawa, T., Benjamin, J., Novak, T., Oppewal, H., Rao, V., 1994. Combining revealed and stated preferences data. Market. Lett. 5, 335–349.
Bhat, C.R., Castelar, S., 2002. A unified mixed logit framework for modeling revealed and stated preferences: formulation and application to congestion pricing analysis in the San Francisco Bay area. Transp. Res. Part B Methodol. 36, 593–616.
Bouman, P., Lovric, M., Li, T., Van Der Hurk, E., Kroon, L., Vervest, P., 2012. Recognizing Demand Patterns from Smart Card Data for Agent-Based Micro-simulation of Public Transport.
Brownstone, D., Bunch, D.S., Train, K., 2000. Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transp. Res. Part B Methodol. 34, 315–338.
BRTA, 2022. Number of Registered Vehicles in Whole Bangladesh. Bangladesh Road Transport Authority.
Bwambale, A., Choudhury, C.F., Hess, S., 2019. Modelling departure time choice using mobile phone data. Transport. Res. Pol. Pract. 130, 424–439.

Bwambale, A., Choudhury, C.F., Sanko, N., 2015. Modelling car trip generation in the developing world: The tale of two cities. In: Transportation Research Board 94th Annual Meeting (No. 15-2108).
Cabrera-Arnau, C., Prieto Curiel, R., Bishop, S., 2020. Uncovering the Behaviour of Road Accidents in Urban Areas, 7. Royal Society open science, 191739.
Čertický, M., Drchal, J., Cuchý, M., Jakob, M., 2015. Fully agent-based simulation model of multimodal mobility in European cities. Proceedings of 2015 International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), pp. 229–236.
Cervero, R., 1996. Mixed land-uses and commuting: evidence from the American housing survey. Transport. Res. Pol. Pract. 30, 361–377.
Cervero, Robert, 2013. Bus Rapid Transit (BRT): An efficient and competitive mode of public transport, Working Paper, No. 2013-01. University of California, Institute of Urban and Regional Development (IURD, Berkeley, CA.
Charypar, D., Nagel, K., 2005. Generating complete all-day activity plans with genetic algorithms. Transportation 32, 369–397.
Chiou, Y.-C., Wen, C.-H., Tsai, S.-H., Wang, W.-Y., 2009. Integrated modeling of car/motorcycle ownership, type and usage for estimating energy consumption and emissions. Transport. Res. Pol. Pract. 43, 665–684.
Currie, G., Delbosc, A., 2013. Exploring comparative ridership drivers of bus rapid transit and light rail transit routes. Journal of Public Transportation 16, 3.
Currie, G., Delbosc, A., 2014. Assessing bus rapid transit system performance in Australasia. Res. Transport. Econ. 48, 142–151.
Deng, T., Nelson, J.D., 2013. Bus Rapid Transit implementation in Beijing: an evaluation of performance and impacts. Res. Transport. Econ. 39, 108–113.
Ding, H., Yang, M., Wang, W., Xu, C., 2018. Simulating and analyzing the effect on travel behavior of residential relocation and corresponding traffic demand management strategies. KSCE J. Civ. Eng. 22, 837–849.
DTCA, 2015. Revised Strategic Transport Plan (RSTP), Dhaka Transport Coordination Authority. (DTCA), Dhaka, Bangladesh.
DTCA, 2015. The Project on the Revision and Updating of the Strategic Transport Plan for Dhaka. Ministry of Communications (MoC), Dhaka, Bangladesh.
DTCB, 2005. Strategic Transport Plan (STP) for Dhaka, Dhaka Transport Coordination Board (DTCB), Final Report. Dhaka, Bangladesh.
Duarte, F., Rojas, F., 2012. Intermodal connectivity to BRT: a comparative analysis of Bogotá and Curitiba. Journal of Public Transportation 15, 1.
Enam, A., 2010. Developing a Comprehensive Mode Choice Model to Capture the Preferences for Mass Rapid Transit in Dhaka. Bangladesh Universiy of Engineering and Technology.
Ettema, D., Furtado, B., Sakowski, P., Tovolli, M., 2014. In: Furtado, B.A., Sakowski (Eds.), Complexity Methods Applied to Transport Planning. PAM & Tovolli, MH, pp. 279–300.
Forward, S.E., 2019. Views on public transport and how personal experiences can contribute to a more positive attitude and behavioural change. Soc. Sci. 8, 47.
Gao, M., Zhou, L., Chen, Y., 2016. An alternative approach for high speed railway carrying capacity calculation based on multiagent simulation. Discrete Dynam Nat. Soc. 2016.
Gkiotsalitis, K., Stathopoulos, A., 2015. A utility-maximization model for retrieving users' willingness to travel for participating in activities from big-data. Transport. Res. C Emerg. Technol. 58, 265–277.
Grether, D., Chen, Y., Rieser, M., Nagel, K., 2008. Integrating a Simple Model for Mode Choice into a Multi-Agent Simulation of Travel Behavior and Traffic Flow.
Habib, K.M.N., 2002. Evaluation of Planning Options to Alleviate Traffic Congestion and Resulting Air Pollution in Dhaka City. Bangladesh University of Engineering and Technology.
Hafezi, M.H., Liu, L., Millward, H., 2019. A time-use activity-pattern recognition model for activity-based travel demand modeling. Transportation 46, 1369–1394.
Han, B., Kim, J., Timmermans, H., 2019. Task allocation and gender roles in dual earner households: the issue of escorting children. Travel behaviour and society 14, 11–20.
Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. Journal of choice modelling 32, 100170.
Hidalgo, D., Graftieaux, P., 2008. Bus rapid transit systems in Latin America and Asia: results and difficulties in 11 cities. Transport. Res. Rec. 2072, 77–88.
Huang, R., 2019. Simulating individual work trips for transit-facilitated accessibility study. Environ. Plan. B Urban Anal. City Sci. 46, 84–102.
Ji, Y., Gao, L., Chen, D., Ma, X., Zhang, R., 2018. How does a static measure influence passengers' boarding behaviors and bus dwell time? Simulated evidence from Nanjing bus stations. Transport. Res. Pol. Pract. 110, 13–25.
Jing, P., You, Q., Chen, L., 2018. Agent-based simulation of children's school travel mode with parental escort decisions. Information 9, 50.
Joseph, L., Neven, A., Martens, K., Kweka, O., Wets, G., Janssens, D., 2021. Exploring changes in mobility experiences and perceptions after implementation of the bus rapid transit system in Dar es Salaam. Case Studies on Transport Policy 9, 930–938.
Kadiyali, L.R., 2010. Traffic Engineering and Transport Planning. Khanna Publishers, Delhi, India.
Kagho, G.O., Balac, M., Axhausen, K.W., 2020. Agent-based models in transport planning: current state, issues, and expectations. Procedia Comput. Sci. 170, 726–732.
Levine, J., Zellner, M., Arquero de Alarcón, M., Shiftan, Y., Massey, D., 2018. The impact of automated transit, pedestrian, and bicycling facilities on urban travel patterns. Transport. Plann. Technol. 41, 463–480.
Li, X.-y., Li, X.-m., Yang, L., Li, J., 2018. Dynamic route and departure time choice model based on self-adaptive reference point and reinforcement learning. Phys. Stat. Mech. Appl. 502, 77–92.
Madlener, R., Sunak, Y., 2011. Impacts of urbanization on urban structures and energy demand: what can we learn for urban energy planning and urbanization management? Sustain. Cities Soc. 1, 45–53.
Makinde, O., Neagu, D., Gheorghe, M., 2018. Agent based micro-simulation of a passenger rail system using customer survey data and an activity based approach. Proceedings of UK Workshop on Computational Intelligence 123–137.
Małecki, K., 2018. A computer simulation of traffic flow with on-street parking and drivers' behaviour based on cellular automata and a multi-agent system. Journal of computational science 28, 32–42.
Manley, E., Cheng, T., Penn, A., Emmonds, A., 2014. A framework for simulating large-scale complex urban traffic dynamics through hybrid agent-based modelling. Comput. Environ. Urban Syst. 44, 27–36.
Manser, P., Becker, H., Hörl, S., Axhausen, K.W., 2020. Designing a large-scale public transport network using agent-based microsimulation. Transport. Res. Pol. Pract. 137, 1–15.
Märki, F., Charypar, D., Axhausen, K.W., 2014. Agent-based model for continuous activity planning with an open planning horizon. Transportation 41, 905–922.
Mavi, R.K., Zarbakhshnia, N., Khazraei, A., 2018. Bus rapid transit (BRT): a simulation and multi criteria decision making (MCDM) approach. Transport Pol. 72, 187–197.
McCormack, G.R., Ghoneim, D., Frehlich, L., Blackstaffe, A., Turley, L., Bracic, B., 2021. A 12-month natural experiment investigating the impacts of replacing a traditional bus service with bus rapid transit on physical activity. J. Transport Health 22, 101239.
McDonnell, S., Zellner, M., 2011. Exploring the effectiveness of bus rapid transit a prototype agent-based model of commuting behavior. Transport Pol. 18, 825–835.
McFadden, D., 1973. Conditional Logit Analysis of Qualitative Choice Behavior.
Mehlstäubler, K., 2019. Implementation of Public Transportation in the MATSim Simulation Environment. Technical University of Munich.
Melo, P.C., Graham, D.J., Canavan, S., 2012. Effects of road investments on economic output and induced travel demand: evidence for urbanized areas in the United States. Transport. Res. Rec. 2297, 163–171.
Moreno, A.T., Michalski, A., Llorca, C., Moeckel, R., 2018. Shared autonomous vehicles effect on vehicle-km traveled and average trip duration. J. Adv. Transport. 2018.
Paget-Seekins, L., 2015. Bus rapid transit as a neoliberal contradiction. J. Transport Geogr. 48, 115–120.
Palacios, M.S., Cochran, A., Bell, C., Jiménez, U.H., Leshner, E., Morales, F.T., Chatman, D.G., 2020. Bus rapid transit arrives in Barranquilla, Colombia: understanding a changing landscape through residents' travel experiences. Travel Behaviour and Society 21, 131–139.
Poku-Boansi, M., Marsden, G., 2018. Bus rapid transit systems as a governance reform project. J. Transport Geogr. 70, 193–202.
Quddus, M., Rahman, F., Monsuur, F., de Ona, J., Enoch, M., 2019. Analyzing bus passengers' satisfaction in Dhaka using discrete choice models. Transport. Res. Rec. 2673, 758–768.
Rahman, F., 2022. Exploring paratransit service quality based on low-income women's perception: a case study in Dhaka city by structural equation model (SEM). IATSS Res. 46, 181–192.
Rahman, M.S.-U., Timms, P., Montgomery, F., 2012. Integrating BRT systems with rickshaws in developing cities to promote energy efficient travel. Procedia-Social and Behavioral Sciences 54, 261–274.
Ramos, S., Vicente, P., Passos, A.M., Costa, P., Reis, E., 2019. Perceptions of the public transport service as a barrier to the adoption of public transport: a qualitative study. Soc. Sci. 8, 150.
Raney, B., Cetin, N., Völlmy, A., Vrtic, M., Axhausen, K., Nagel, K., 2003. An agent-based microsimulation model of Swiss travel: first results. Network. Spatial Econ. 3, 23–41.
Rashedi, Z., Mahmoud, M., Hasnine, S., Habib, K.N., 2017. On the factors affecting the choice of regional transit for commuting in Greater Toronto and Hamilton Area: application of an advanced RP-SP choice model. Transport. Res. Pol. Pract. 105, 1–13.
Rastogi, R., 2000. Stated Preference Survey: Experience from Developing Country. Department of Civil Engineering, Engineering College, KOTA Mumbai, India. *Unpublished report*.
Sajib, S.H., 2021. A Qualitative case study on inadequate public transport system and its social impact on people in Dhaka. Transactions on Transport Sciences 12.
Sanko, N., 2014. Travel demand forecasts improved by using cross-sectional data from multiple time points. Transportation 41, 673–695.
Satiennam, T., Jaensirisak, S., Satiennam, W., Detdamrong, S., 2016. Potential for modal shift by passenger car and motorcycle users towards Bus Rapid Transit (BRT) in an Asian developing city. IATSS Res. 39, 121–129.
Satu, S.A., Chiu, R.L., 2019. Livability in dense residential neighbourhoods of Dhaka. Hous. Stud. 34, 538–559.
Schalekamp, H., Behrens, R., 2010. Engaging paratransit on public transport reform initiatives in South Africa: a critique of policy and an investigation of appropriate engagement approaches. Res. Transport. Econ. 29, 371–378.
Shabanpour, R., Golshani, N., Auld, J., Mohammadian, A., 2017. Dynamics of activity time-of-day choice. Transport. Res. Rec. 2665, 51–59.
Shafi, R., Delbosc, A., Rose, G., 2022. The Role of Culture and Evolving Attitudes in Travel Behaviour Assimilation Among South Asian Immigrants in Melbourne, Australia. Transportation, pp. 1–27.
Shi, X., Moudon, A.V., Hurvitz, P.M., Mooney, S.J., Zhou, C., Saelens, B.E., 2021. Does improving stop amenities help increase Bus Rapid Transit ridership? Findings based on a quasi-experiment. Transp. Res. Interdiscip. Perspect. 10, 100323.
Siddique, M., Bakkar, A., Choudhury, C.F., 2017. Modelling the behavioural response to congestion pricing in Dhaka, Bangladesh. Transportation in Developing Economies 3, 1–13.
Train, K.E., 2009. Discrete Choice Methods with Simulation. Cambridge university press.

TYPSA, 2019. Feasibility Study and Preliminary Design for Construction of Dhaka Subway. Dhaka.

Västberg, O.B., Karlström, A., Jonsson, D., Sundberg, M., 2020. A dynamic discrete choice activity-based travel demand model. Transport. Sci. 54, 21–41.

Venter, C., Jennings, G., Hidalgo, D., Valderrama Pineda, A.F., 2018. The equity impacts of bus rapid transit: a review of the evidence and implications for sustainable transport. International Journal of Sustainable Transportation 12, 140–152.

Vickrey, W.S., 1969. Congestion theory and transport investment. Am. Econ. Rev. 59, 251–260.

Vosooghi, R., Puchinger, J., Jankovic, M., Sirin, G., 2017. A critical analysis of travel demand estimation for new one-way carsharing systems. In: Proceedings of 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), pp. 199–205.

Wadud, Z., 2020. The effects of e-ridehailing on motorcycle ownership in an emerging-country megacity. Transport. Res. Pol. Pract. 137, 301–312.

Wee, B., Kroesen, M., 2022. oAttitude changes, modelling travel behaviour, and ex ante project evaluations. Transp. Res. Interdiscip. Perspect. 16, 100724.

World Bank, 2015. Open Transport Development and Integration of ICT and Transport.

Yagi, S., Mohammadian, A., 2008. Policy simulation for new BRT and area pricing alternatives using an opinion survey in Jakarta. Transport. Plann. Technol. 31, 589–612.

Yagi, S., Mohammadian, A.K., 2010. An activity-based microsimulation model of travel demand in the Jakarta metropolitan area. Journal of Choice Modelling 3, 32–57.

Zgheib, N., Abou-Zeid, M., Kaysi, I., 2020. Modeling demand for ridesourcing as feeder for high capacity mass transit systems with an application to the planned Beirut BRT. Transport. Res. Pol. Pract. 138, 70–91.

Zhang, S., Zhao, J., 2018. Low-carbon futures for Shenzhen's urban passenger transport: a human-based approach. Transport. Res. Transport Environ. 62, 236–255.

Zmud, J.P., Sener, I.N., 2017. Towards an understanding of the travel behavior impact of autonomous vehicles. Transport. Res. Procedia 25, 2500–2519.

Zou, M., Li, M., Lin, X., Xiong, C., Mao, C., Wan, C., Zhang, K., Yu, J., 2016. An agent-based choice model for travel mode and departure time and its case study in Beijing. Transport. Res. C Emerg. Technol. 64, 133–147.