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Impact of COVID-19 on mode choice behavior: A case study for Dhaka, Bangladesh

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ABSTRACT

To ensure safety against the COVID-19, along with all other countries, Bangladesh as a least-developed country needs to deal with the changes in travel behavior, particularly changes in mode choice behavior. As Dhaka has been marked as a hotspot for the virus contagion, this paper has focused on the changes in mode choice behavior of Dhaka people due to the COVID-19 pandemic while they are on the road. A web-based questionnaire survey was conducted to capture the information on mode preferences and perspectives on travel characteristics for commute and discretionary trips before and during COVID-19. Multinomial Logit (MNL) model based on a utility function has been used to investigate the significance of the socio-demographic attributes and travel characteristics of the trips on the mode choice behavior and to calculate the maximum utility of the mode choice. This study highlighted some noticeable changes in perspective towards mode choice. People prefer walking, private vehicles, and rickshaw more during the pandemic as they feel these modes are more reliable, available, and cost-effective in this crucial time. Usage of public transportation dropped drastically for discretionary purposes. Additionally, usage of the on-demand vehicle increased during the pandemic as a large portion of commuters shifted to on-demand vehicles from public transportation. Furthermore, this paper suggested some viable policy-making implications to cope with the current pandemic and relatable future national and global crises. Finally, the paper concludes by suggesting some future research insights.

1. Introduction

COVID-19 pandemic has brought new challenges to the urban transportation system by highlighting the weaknesses of the current transportation modes to deal with the contamination against the virus. As the SARS-CoV-2 virus can live on hard surfaces for several hours (Doremalen, et al., 2020), it increased the risk of contagion while traveling. As a result, all shared mobility sectors including public transportation were severely affected by this recent pandemic (Tarasi et al., 2021). Numerous studies observed significant modal shifts and noticeable decline in the usage of public transportation during the pandemic (Abdullah et al., 2020; Schmidt et al., 2021; Eisenmann et al., 2021; Politis et al., 2021; Bin et al., 2021).

Dhaka, a developing country, has observed over 1550 thousand COVID-19 cases and over 27 thousand deaths (1st October) (JHU, 2021). As a precaution measure against the virus transmission, lower usage of public transportation and shared modes (ride-hailing services), and a significant increase in private vehicles and non-motorized mode usage during the COVID-19 crisis were observed in the country (Zannat et al., 2021; Jamal and Paez, 2020; Anwari et al., 2021). Similar incidents were also observed in the neighboring country of India (Zannat et al., 2021; Meena, 2020).

More than half (55 %) of the global population lives in urban areas. By the year 2050, 68 % of the global population will live in urban areas (UN DESA, 2018). Several studies also exposed the vulnerability of urban people to COVID-19 as more acute than people living in rural areas (Carozzi et al., 2020; Acuto, 2020). Areas with higher population density are more vulnerable to contagious diseases like these. According to the detected COVID-19 cases within a 3 weeks duration timeframe, urban counties in the USA showed a higher infection rate for coronavirus compared to the rural counties (Paul et al., 2020).

Dhaka has been dealing with the pandemic since March 8th,
2020 when the first case of coronavirus was detected (WHO, 2020). The country has gone through several phases of lockdowns to contain the infection rate. Later on, to prevent the adverse impact of the restriction on the economy, Bangladesh, like many other developing countries, relaxed the lockdowns through several measures (Guoyuan and Hu, 2020) such as imposing several restrictions on the transportation system. Public transports resumed on 1st June 2020 with occupancy reduced to 50% of vehicle capacity (TheDailyStar, 2021). With a lower infection rate, the restrictions were withdrawn on 1st September 2020. Following a lower infection rate, Bangladesh started to vaccinate people
on 7th February 2021 (Sakib, 2021). While the 2nd wave is still active in the country the Government declared the relaxation of lockdown and withdrew the previously imposed restrictions on the transportation system from August 11th, 2021 (DhakaTribune, 2021).

The continuous cycle of implementation and relaxations of lockdowns and travel restrictions in Bangladesh has a certain possibility to impact the mode choice behavior of the people in this country. In the capital city Dhaka, it is challenging for public transport users to maintain their protective measures while traveling through the city for daily purposes. A major portion of these city dwellers are involved in unorganized labor and additionally, around 800,000 people are involved in textile industries (Worldpopulationreview, 2021), which made it harder for them to avoid public transport and maintain personal protections. These circumstances necessitate the need for intense and dedicated research on the mode choice behavior of the people of Dhaka.

The prime objectives of the transport planners would be to meet the demand for preferred transport modes supply during the pandemic. Mode choice analysis is a vital step for estimating the travel demand through a four-stage modeling process. Multinomial Logit Model (MNL) is traditionally used for mode choice behavioral analysis which requires crisp values of the variable for analysis (Pulugurta, Arun, and Erramalli, 2013). Multinomial Logistic Regression can analyze the mixed nature of data. Utilizing the maximum likelihood ratio MNL estimates the probability of the dependent variables (Robin, 2014). Additionally, it does not assume normality, linearity, or homoscedasticity which makes MNL a good choice for mode choice modeling (Starkweather and Moske, 2005).

Several studies around the world have portrayed significant accuracy of MNL for predicting mode choice behavior. Lee et al. (2018) compared MNL with four types of Artificial Neural Network (ANN) where MNL obtained a prediction accuracy of 70 % (Lee et al., 2018). In another study for mode choice analysis, MNL was compared to Extreme Gradient Boosting (XGB) model which uses machine learning. It showed great explanatory power and strong consistency between training and testing (XGB) model which uses machine learning. It showed great explanatory power and strong consistency between training and testing. The researchers here ran both of the models 100 times while explaining power and strong consistency between training and testing.

MNL models have a prediction accuracy of 94.5 % and 92.7 % respectively (Lee et al., 2018). In another study using MNL for analyzing the mode choice behavior of private university students in Dhaka (Nasrin, 2019). Among them, discrete choice models are widely used in transportation models to evaluate modal choice predictability and for validation purposes where MNL had an accuracy of 72.6 % and 76.2 % respectively (Hussain et al., 2017). In Bangladesh, a few types of research on mode choice analysis using MNL were found. In 2018, Rahman and Baker studied the impact of constructions of flyover infrastructures on the mode switch behavior (Rahman and Baker, 2018). Another study uses MNL for analyzing the mode choice behavior of private university students in Dhaka (Nasrin, 2020). In the pre-COVID times, Rahman et al. (2020a) studied the mode choice behavior of Dhaka city using MNL. Their study was focused on selected areas covering the under-construction Metro Rail Transit Line-1 route (Rahman et al., 2020a). During the COVID-19 pandemic, Zafri et al. (2021) explored the impact of the pandemic on active travel mode choice using MNL (Zafri et al., 2021b). Based on our searching attempts for research articles through several academic sources (Scopus, Web of Science, and Google Scholar) with a similar focus to ours, we can mention that no similar research was conducted on the transportation mode users of Dhaka city to date. Several studies have been done to find out the impact of mode choice behavior due to the COVID-19 pandemic in countries with similar socio-economic demographics. Studies in Pakistan indicated social distancing, availability of hand sanitizers, cleanliness, comfort, and infection concerns are influencing factors when choosing a mode of traveling (Abdullah et al., 2021a; Abdullah et al., 2022). Another study in a similar area indicated people tend to travel solo than travel in public transport (Abdullah et al., 2021b). In India, walking, bicycling, and private transportation usage are preferable during the pandemic (Meena, 2020).

In this context, this research is subjected to finding out the changes in transportation mode choice behavior due to the COVID-19 pandemic. Additionally, depending on the findings some insightful deliberate recommendations have been provided to assist the policymakers in taking necessary provisions to keep the transportation network of Dhaka effective during the COVID-19 pandemic or any future pandemics.

2. Model structure

Usually, a decision-maker is faced with a set of alternatives, known as a choice set, each of which is characterized by different attributes. To choose the preferred alternative, the decision-maker needs a decision rule to process. One of the four categories of the decision rule is based on Utility Maximization Rule.

2.1. Basic construction of utility theory

The utility of an alternative is an objective function of the attribute vectors and the decision-maker characteristics which can be represented as:

\[ U(Z_i, S_t) = \] (1)

where,

\[ U (\cdot) = \text{mathematical utility function}. \]

\[ Z_i = \text{vectors of attributes describing alternate } i \text{ and } \]

\[ S_t = \text{Socio-economic characteristics of the decision-maker } t. \]

The utility of a travel mode is generally referred to as the attractiveness of an alternative for a specific trip and the decision-maker mainly chooses the alternative with the highest utility. This can be stated as an alternative, ‘i’ will be preferred if the utility value of ‘i’ is greater than or equal to the utility of all alternatives ‘j’ (Sekhar, 2014). (Ben-Akiva and Lerman, 1985) explained that the total utility can be made operational by separating it into deterministic (observable) and random (error) components. Equation (2) represents the utility function for the chosen alternative ‘i’.

\[ U_i = V_i + \varepsilon_i \] (2)

where:

\[ U_i = \text{is the utility function of the alternative } 'i'. \]

\[ V_i = \text{is the deterministic or observable portion of the utility estimated by the analyst, and.} \]

\[ \varepsilon_i = \text{is the error or the portion of the utility unknown to the analyst.} \]

Since \( \varepsilon \) is the error portion of the utility, the general utility can be expressed as the function of \( V \). Combining the vectors \( Z_a \) and \( S_t \) a new vector \( x \) can be defined. Hence, \( V_{in} \) can be written as \( V(x) \).

\[ V_{in} = \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} \] (3)

Equation (3) can be used to estimate the utility value of the mode choices defined by the coefficient of the independent variables. The independent variables for this study are (a) characteristics of the trip makers (gender, income, occupation, car availability in the household) and (b) characteristics of the transport facility (reliability, availability, cost-effectiveness).

2.2. Multinomial Logit model

Based on utility maximization theory, models were developed to identify the individual’s choices among the alternatives (Puan et al., 2019). Among them, discrete choice models are widely used in transportation applications. Depending upon the functional form of the error
term distribution, discrete choice models are of three types: Logit model, Probit Model, and General Extreme Value (GEV) Model. Logit models can represent systematic taste variation very well (Train, 2003) and are analytically more convenient. When the number of alternatives in the choice set is greater than two and the dependent variable consists of several categories that are not ordinal, multinomial logit (MNL) models are used to model relationships between the polymomial variables and the set of independent variables. There are three assumptions to formulate the MNL. Firstly, the random components of the alternative variables and the set of independent variables. There are three Probit Model, and General Extreme Value (GEV) Model.

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Since the option in the Google form that respondents must answer all the questions to move on to the next section of the survey was kept on, there was no hassle to deal with incomplete responses. The URL link to the form was then circulated among the people living in Dhaka City through various social media platforms (WhatsApp and Facebook Messenger) and electronic mail. Similar data collection procedure has been performed by (Anwar et al., 2021; Paul et al., 2021). After manually data screening with care, the survey carried out between 1st April 2021 to 15th June 2021 (10 weeks) produced 571 response sets.

The questionnaire survey of the study included 3 sections. The first section extracted details on socio-demographic characteristics of the trip-makers—Gender, Age, Net Monthly Income (NMI), Occupation, and Vehicle ownership. The second section of the questionnaire was designed to ask about the information related to travel modes usage for regular day situations (Before COVID-19 infection) and the final section collected information about the travel modes usage for the COVID situation (During COVID-19).

3.2. Sample characteristics

Demographic attributes of the respondents of the questionnaire survey are summarized in Table 1 which shows most respondents are male (57.8 %) and the dominant age group is 26–60 years (43.6 %). Majority of the respondents (41.7 %) were low-income people (0–15,000 bdt). In this study, the sub-category of occupation, “Others” is comprised of self-employed, freelancers, unemployed and undefined occupations. In terms of occupation, students (34.5 %) are the most active respondents. Around 54 % of the respondents of this study own vehicles which is quite alarming in response to sustainable transportation. Out of them, almost 25 % of people own a car and nearly 5 % of them have two cars. The percentage of motorbike owners (20 %) is also fairly high and around 3 % of people have two. A different scenario can be seen for the cycle. Less than 10 respondents have only one cycle and around 1 % of respondents have two cycles. This is because the pandemic has forced many people to purchase motorcycles compared to the period before the COVID-19 infection (Zafri et al., 2021b).

4. Results and discussion

4.1. Descriptive analysis

This section outlines the analysis of responses related to the mode usage and insights into the trip-related factors applied in the model specifications. In this study, a trip for commute purposes refers to travel between one’s place of residence and place of work or study and discretionary activities signify shopping, exercise, leisure, social visits, etc.

Table 1

| Items                  | Sub-categories | Frequency | Percentages |
|------------------------|----------------|-----------|-------------|
| Gender                 | Male           | 330       | 57.8        |
|                        | Female         | 241       | 40.2        |
| Age                    | 0–18 years     | 46        | 8.1         |
|                        | 19–25 years    | 210       | 35.2        |
|                        | 26–60 years    | 249       | 43.6        |
|                        | 60 + years     | 75        | 13.1        |
| Net Monthly income (NMI) | 0–15,000     | 238       | 41.7        |
|                        | 15,000–40,000  | 178       | 31.2        |
|                        | 40,000+        | 155       | 27.1        |
| Occupation             | Student        | 197       | 34.5        |
|                        | Service        | 141       | 24.7        |
|                        | Business       | 110       | 19.3        |
|                        | House-wife     | 28        | 4.9         |
|                        | Others         | 95        | 16.6        |
| Vehicle ownership      | Yes            | 46        | 7.2         |
|                        | Motorbike      | 115       | 18.1        |
|                        | Car            | 139       | 22.9        |
|                        | No             | 262       | 45.9        |

*NMI = Net Monthly Income.
*BDT = Bangladesh Taka.
etc. A similar classification of trip purpose has been defined by (Bhaduri et al., 2020). Fig. 2 represents the percentage usage of the different modes for work and discretionary activities before COVID-19 and during the COVID-19 situation. It can be seen that there is a rise in making no trips during the pandemic as expected, but the increase is not that large. This is because people still go to work physically, particularly those in manual labor jobs (Politis et al., 2021). In addition, there is a jump in walking activity for discretionary purposes. An increase in walking activity has been observed in many other studies too (Luan et al., 2021). Fig. 2 also reveals a drop in public transport (30 % to 17.7 % for commute activity and 20 % to 13.3 % for discretionary activity) probably because of own safety concerns and being unable to maintain safe physical distance while traveling with strangers in buses or leguna. However, it is interesting to find that on-demand vehicle usage for commuting grew during the pandemic. For commuting, even though there is a slight decrease, a private vehicle is still the top usage among all modes. During the COVID-19 crisis, NMV is the only category of mode to increase its usage for both purposes. Rickshaw can be a suitable mode of transport in Bangladesh as it is pollution-free and cost-effective for short-distance movement for people not owning personal vehicles during COVID-19. Similar results for NMV have been found in other studies too (Anwari et al., 2021).

The level of inertia to retain the usual mode as the prime mode for both purposes and the changes in travel mode usage due to COVID-19 has been analyzed by using Sankey diagrams as represented in Figs. 3 (a) and 3(b).

It is manifest from Fig. 3(a) that a large proportion of public transport usage has been shifted to on-demand vehicles, followed by the category “No Trip” and non-motorized vehicles. This is in response to restrictive measures imposed by the Government (Ahmed, 2021) and of own safety concerns against the spreading of the virus. During the COVID-19 crisis, users from every mode of travel shifted to the “No Trip” category. This is possibly due to an inclination to work from home services and online activities for educational purposes (Rahman et al., 2020b). However, the preference for walking activity in the COVID situation is not as expected in other studies (Khaddar and Fatmi, 2021; Luan et al., 2021).

Likewise, in commute activities, a large percentage of public transport usage has been shifted to on-demand vehicles for discretionary activities. A decent portion of private users also feels uninterested to make a discretionary trip. This is perhaps because of the increase in online shopping facilities (Khan and Bhuiyan, 2021) and the soar in social media usage (Kemp, 2021). During the pandemic, a slight amount of users shifted to walking for discretionary activity. The low rise in pedestrian activity might be due to insufficient walking facilities in Dhaka City (Morshed, 2021).

Figs. 4(a) and (b) depict the changes in the perspective of the respondents on the characteristics of the primary mode chosen for commute and discretionary activity before and during COVID-19. In this study, three features related to the mode of transport were selected: reliability, availability, and cost-effectiveness for both purposes using a 5-point Likert scale which categorized as very poor, poor, neutral, good, and excellent. Reliability of the model refers to the quality of being safe and performing effectively to reach the destination in the expected time. Availability of the mode denotes whether the mode of transport is available or not during the time to initiate the trip weekly. Finally, the cost-effectiveness of the mode signifies how costly it is to use the chosen mode to travel a specific distance. Maintenance and fuel costs in terms of private vehicles, fares in terms of public transport, on-demand vehicles, and rickshaws are considered as the travel cost.

For commute activity, private vehicle, non-motorized vehicle, and walking seems to be more reliable to the trip-makers during the pandemic. While public transport is the least reliable mode in the pandemic, its availability increased negligibly. Bus and leguna users of Dhaka City seem very unsatisfied with the reliability and availability of the public transport because mostly it remains over-crowded with passengers and the frequency of bus service is not quite good (Rahman, 2011). According to the respondents, the highest rating for cost-effectiveness belongs to non-motorized vehicles. It can be hypothesized that rickshaws is playing an important role to maintain the transportation of commuters every day.

According to Fig. 4(b), the rating of walking as a reliable mode of discretionary travel has rocketed during this pandemic along with on-demand vehicles, particularly bike-hailing services, because of being the fastest mode of transportation (IDLC, 2017). The availability of the on-demand vehicles also jumped in this pandemic as the purchase of motorcycles has soared (Zafri et al., 2021a) and many people in Bangladesh are selecting to become riders to earn their living (IDLC, 2017). However, respondents do not feel on-demand vehicles as a cost-effective mode for discretionary activities. Based on the response, the majority of respondents chose walking as an excellent cost-effective mode when it comes to making trips for discretionary purposes. Besides that, non-motorized vehicles also gained popularity as a cost-effective mode to travel for discretionary activity in the COVID-19 pandemic.

4.2. Model estimation and results

The multinomial logit model was used to estimate the coefficients using the utility function and identify the significance of the socio-demographic characteristics and mode attribute variables on the mode choice behavior for commute and discretionary trip purposes before and
The nominal outcome variable for each model was the type of mode chosen for each trip purpose. For commute activity models, the “No Trip” category was set as the reference category and for discretionary activity models, the “Not interested” category was applied as the reference category to compare the parameter estimate of each type of mode with when using no mode at all. The decoding of the independent variables used in the model development has been presented in Table 2.

4.2.1. Checking the selected model based on commute activity

Table 3 contains the Likelihood Ratio chi-square test, comparing the full model (containing all the predictors) against a null (or intercept only model). Statistical significance for both before ($\chi^2 = 683.605$, Sig. less than 0.05) and during $(\chi^2 = 596.066$, Sig. less than 0.05) the pandemic indicates that the full model is a significant improvement in fit over the null model. It also presents the Deviance and Pearson chi-square tests, also known as the goodness-of-fit of the statistical model, which describes how well a model fits into a set of data. Since, non-significant test results indicate that the model fits the data well, the Deviance chi-square test for both before and during the pandemic shows that the data and the model predictions were similar. However, Pearson’s chi-square test was significant both before and during COVID-19. To assess the goodness-of-fit model, the pseudo R-square has been examined. R-square briefs the proportion of variance in the dependent variable associated with independent variables (Al-Salih and Esztergár-Kiss, 2021).

Fig. 3a. Inertia in various modes of travel for commute activities.

Fig. 3b. Inertia in various modes of travel for discretionary activities.

during COVID-19. The nominal outcome variable for each model was the type of mode chosen for each trip purpose. For commute activity models, the “No Trip” category was set as the reference category and for discretionary activity models, the “Not interested” category was applied as the reference category to compare the parameter estimate of each type of mode with when using no mode at all. The decoding of the independent variables used in the model development has been presented in Table 2.

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4.2.2. Parameter estimates of model for commute activity

As shown in Table 4, the ‘Estimate’ column represents the regression coefficients expressed in the metric of log-odds, the ‘Exp. (B)’ column denotes the odds ratios and the ‘Sig.’ column shows the statistically significant level of the independent variables. The odds ratio indicates the factor, the odds of a person choosing a particular mode changes for every-one-unit increase on an independent variable, while other independent variables remain constant. Independent variables having a statistically significant level of less than 0.05 is a significant predictor of the model.

The first set of coefficients represents comparisons between NMV users for commuting and those making no commute trips. Apart from ‘occupation’, ‘vehicle ownership’, ‘availability’ and ‘cost effectiveness’ for before and ‘age’, ‘occupation’, ‘vehicle ownership’, ‘reliability’, ‘availability’ and ‘cost effectiveness’ for during the pandemic, the remaining variables are significant predictors in the model. The second set of coefficients represents comparisons between on-demand vehicle users and those making no commute trips. ‘Age’, ‘NMI’, and ‘reliability’ for before and only ‘NMI’ and ‘cost effectiveness’ for during the COVID-19 are the significant predictors in the model. The estimate of ‘age’ is negative for before COVID-19, indicating that older persons were more likely to use no mode at all than to choose on-demand vehicles. The odds ratio of 0.338 indicates that for every-one level increase of category ‘age’, the odds of a person choosing on-demand vehicles changes by a factor of 0.338. On the contrary, the estimate of ‘NMI’ is positive in both situations, indicating that people with high income are more likely to choose on-demand vehicles in both situations. The odds ratio of 8.854 for before and 3.100 during the pandemic indicates that for every-one level increase of category ‘NMI’, the odds of a person choosing on-demand vehicles changes by a factor of 8.854 and 3.100 respectively. The odds ratio of 0.524 indicates that for every-one level increase of category ‘reliability’, the odds of a person choosing on-demand vehicles changes by a factor of 0.524. The third set of coefficients represents comparisons between private transport users for commute trips and those making no commute trips. ‘Occupation’ and ‘cost effectiveness’ for before and ‘age’ ‘occupation’, ‘reliability’ and ‘cost effectiveness’ for during the COVID-19 are the insignificant variables in the model. The fourth set of coefficients represents comparisons between public transport users for commute activities and those making no commute trips. ‘Gender’, ‘age’, ‘NMI’, ‘vehicle ownership’,

Fig. 4a. Temporal Comparison of Mode Characteristics perspective for commute activity.
availability' and 'cost effectiveness' for before and 'gender', 'age', 'vehicle ownership' and 'reliability' for during pandemic are the significant predictors in the model. The variables 'Gender', 'vehicle ownership', 'reliability', and 'cost effectiveness' has negative estimates for both period, meaning as persons scoring higher on these variables were less likely to choose public transport. The final set of coefficients represents comparisons between users who walk for commuting and those making no commute trips. Here, 'occupation', 'reliability' and 'availability' was not a significant predictor for before whereas for during the COVID-19 crisis 'NMI', 'occupation', 'reliability', 'availability', and 'cost-effectiveness are the insignificant predictors. It is manifest from the model that the occupation of the trip-makers is not a significant variable to influence the mode choice behavior for commute trips. The MNL model classified 67.3 % and 55 % of the cases correctly for before and during COVID-19 trips for commute activity, respectively as shown in Table 5 and 6.

4.2.3. Checking of the selected model based on discretionary activity

Table 7 shows that statistical significance for both before and during the pandemic shows that the data and the model predictions were similar. Similar to the model for commute activity, the Pearson’s chi-square test was significant for both before and during COVID-19.

4.2.4. Parameter estimates of model for discretionary activity

From Table 8, it can be seen that the first set of coefficients represents comparisons between NMV users for discretionary trips and those making no discretionary trips. 'Availability' for before and 'gender' for during the pandemic is the only significant predictor in the model. The second set of coefficients represents comparisons between on-demand vehicle users and those who are uninterested in discretionary trips. 'Availability' for before and 'gender', 'reliability', and 'cost effectiveness' for during the pandemic, are the only significant predictors in the model. The estimate of 'availability' is positive for before COVID-19, indicating that people were likely to use more on-demand vehicles if they were more available. On the contrary, the estimate of 'gender' is negative for during COVID-19, indicating that females are more likely to be uninterested in discretionary activities than to choose on-demand vehicles for discretionary trips. The third set of coefficients represents comparisons between private transport users and those having no interest in making trips for discretionary activities. 'NMI', 'vehicle
The ongoing COVID-19 pandemic has brought unconventional changes to every aspect of regular human interactions across the world. The pandemic markedly made an impact on the daily mobility pattern. It has created doubts and disputes about the capacity of the existing transportation system to deal with the pandemic and similar global crises.

To contain virus contagion through mobility, significant restrictions were imposed on several travel modes while the lockdowns were eased. As a major transport mode, emphasized restrictions on public transport were imposed in different cities, and eventually, frequencies of public transport services were reduced. These have made it difficult for the low-income people who do not own a private vehicle to access their respective jobs conveniently. On the contrary, the increasing amount of private mode usage for several trip purposes decreases the effectiveness of roadway capacity and eventually results in increased traffic congestion. This particular mode shifting behavior initiates the risk of an unsustainable development for the developing megacities where the dominant mode could be private cars (Shakibaei et al., 2021). In the neighboring country India, 5.3% of commuters shifted from public transport to private ones (Pawar et al., 2020). Needless to say, more automobiles on the street mean more air pollution. Therefore, the prime focus of the transport planners should be to come up with a remedial plan that would be sustainable enough to divert the private mode users and would resolve the doubts of the regular users of public transport for considering the usage of public modes during the pandemic.

The concern of this study is to investigate the changes in mode choice behavior for commute or discretionary travel purposes of the residents of Dhaka due to the COVID-19 pandemic. Results from the analysis marked public transport as the least reliable during the pandemic and also signifies a remarkable drop in the usage of public transport. This could be because of the captive environment of public modes which increases the possibility of virus infection. As a remedy to this, public transport could be redesigned including a proper ventilation system which will decrease the chance of virus contagion. A study by the University of Colorado Boulder shows a 0% chance of getting infected in a well-ventilated metro after the first 70 min of a ride and the rate for contagion is lower for a bus (Maya Wei-Haus and Kennedy Elliott, 2020). To regain commuters’ faith in public transportation increased facilities should be attributed. The UK authorities reconfigured sitting arrangements, and ventilation systems and installed contactless door sensors, hand sanitizing dispensers, and clear screens between seats to provide

### Table 3
Model fitting information, Goodness-of-fit, and the Pseudo R-Square for commute activity trip.

| Model               | Model Fitting Criteria | Likelihood Ratio Tests |
|---------------------|------------------------|------------------------|
|                     |                        | –2 Log-Likelihood      | Chi-Square | df | Sig. |
| Before COVID-19     | Intercept Only Final   | 1643.861               | 683.605    | 40 | 0.000 |
|                     |                        | 960.256               | 2846.228   | 2025 | 0.000 |
|                     |                        | Chi-Square            | df         | Sig. |
|                     |                        | Pearson               | Deviance   | Cox and Snell | Nagelkerke | McFadden |
|                     |                        |                       |            | 0.698 | 0.722 | 0.389 |
| During COVID-19     | Intercept Only Final   | 1746.563              | 596.066    | 40 | 0.000 |
|                     |                        | 1150.496             | 2210.795   | 1885 | 0.000 |
|                     |                        | Chi-Square            | df         | Sig. |
|                     |                        | Pearson               | Deviance   | Cox and Snell | Nagelkerke | McFadden |
|                     |                        |                       |            | 0.648 | 0.671 | 0.310 |

5. Policy implications

The concern of this study is to investigate the changes in mode choice behavior for commute or discretionary travel purposes of the residents of Dhaka due to the COVID-19 pandemic. Results from the analysis marked public transport as the least reliable during the pandemic and also signifies a remarkable drop in the usage of public transport. This could be because of the captive environment of public modes which increases the possibility of virus infection. As a remedy to this, public transport could be redesigned including a proper ventilation system which will decrease the chance of virus contagion. A study by the University of Colorado Boulder shows a 0% chance of getting infected in a well-ventilated metro after the first 70 min of a ride and the rate for contagion is lower for a bus (Maya Wei-Haus and Kennedy Elliott, 2020). To regain commuters’ faith in public transportation increased facilities should be attributed. The UK authorities reconfigured sitting arrangements, and ventilation systems and installed contactless door sensors, hand sanitizing dispensers, and clear screens between seats to provide

### Table 2
Decoding of the independent variables in the model.

| Variable Name       | Decoding of the variables |
|---------------------|---------------------------|
| Gender              | Male = 0, Female = 1      |
| Age                 | 0-18 = 0, 19-25 = 1, 26-30 = 2, 30-40 = 3 |
| NMI                 | 0-15,000 BDT = 0, 15,001 to 40,000 BDT = 1, 40,001 + BDT = 2 |
| Occupation          | Service = 0, Businessman = 1, Student = 2, Housewife = 3, Others = 4 |
| Vehicle ownership   | No = 0, Yes = 1           |
| Reliability         | Very Poor = 0, Poor = 1, Neutral = 2, Good = 3, Excellent = 4 |
| Availability        | Very Poor = 0, Poor = 1, Neutral = 2, Good = 3, Excellent = 4 |
| Cost-effectiveness  | Very Poor = 0, Poor = 1, Neutral = 2, Good = 3, Excellent = 4 |

ownership' and 'availability' for before and 'gender', 'reliability' and 'availability' for during the COVID-19 are the significant variables in the model. The fourth set of coefficients represents comparisons between public transport users and those making no discretionary trips. Only 'gender' and 'cost-effectiveness' are the significant predictors in the model for before and only 'gender' for during pandemic scenarios. The variable 'gender' has negative estimates in both timelines, meaning females are less likely to choose public transport irrespective of the situation. The odds ratio of 0.229 for before and 0.413 for during the pandemic indicates that when the person is female, the odds of that persons choosing public transport change by a factor of 0.229 and 0.413 respectively. The final set of coefficients represents comparisons between users who walk for discretionary activities and those not interested in discretionary trips. Here, only 'cost effectiveness' is the significant predictor for both situations. Similar to the model for commute activities, the occupation of the trip-makers is not a significant variable in this model to influence the mode choice behavior for discretionary activity trips. The MNL model predicted 68.7% and 61.6% of the cases correctly for before and during COVID-19 trips for discretionary activity, respectively as shown in Table 9 and 10.

### Table 3
Model fitting information, Goodness-of-fit, and the Pseudo R-Square for commute activity trip.

| Model               | Model Fitting Criteria | Likelihood Ratio Tests          |
|---------------------|------------------------|---------------------------------|
|                     |                        | –2 Log-Likelihood, Chi-Square, df, Sig. |
| Before COVID-19     | Intercept Only Final   | 1643.861, 683.605, 40, 0.000 |
|                     |                        | 960.256, 2846.228, 2025, 0.000 |
|                     |                        | Chi-Square, df, Sig.            |
|                     |                        | Pearson, Deviance               |
|                     |                        | 0.698, 0.722, 0.389             |
| During COVID-19     | Intercept Only Final   | 1746.563, 596.066, 40, 0.000   |
|                     |                        | 1150.496, 2210.795, 1885, 0.000|
|                     |                        | Chi-Square, df, Sig.            |
|                     |                        | Pearson, Deviance               |
|                     |                        | 0.648, 0.671, 0.310             |
barriers to airborne diseases (Graeme Paton, 2020). Again in the process to incorporate public transport with social distancing measures, reduced efficiency of the public transportation system was observed. As an immediate response, the city of Manila Philippines introduced a segregated lane for Bus Rapid Transit without additional fares that reduced the travel time from 2 to 3 h to 45 min on certain routes (Hasselwander et al., 2021). Furthermore, the installation of a contactless Mobile Finance System (MFS) for payment would also be an alluring measure to be taken as it minimizes the chances of human contact.

A minor shift to walking activities for discretionary purposes was observed which necessitates the demand for well-constructed footpaths in the city. Although a pedestrian-friendly environment is not ensured in

Table 4
Estimation results for commute activities model.

| Mode of transport | Independent variables | Before-COVID | During-COVID |
|-------------------|-----------------------|--------------|--------------|
|                   | Estimate | Sig. | Exp.(B) | Estimate | Sig. | Exp.(B) |
| Non-motorized Vehicle | Intercept | 0.515 | 0.641 | −2.342 | 0.000 |
|                    | Gender | −1.246 | 0.035 | 0.288 | −1.031 | 0.002 |
|                    | Age | −1.232 | 0.001 | 0.292 | 0.415 | 0.099 |
|                    | NMI | 1.733 | 0.004 | 5.659 | 0.787 | 0.014 |
|                    | Occupation | 0.214 | 0.405 | 1.239 | −0.258 | 0.080 |
|                    | Vehicle ownership | −0.514 | 0.356 | 0.596 | 0.356 | 0.290 |
|                    | Reliability | 0.709 | 0.046 | 2.031 | 0.352 | 0.145 |
|                    | Availability | 0.073 | 0.843 | 1.075 | 0.347 | 0.206 |
|                    | Cost-effectiveness | 0.464 | 0.154 | 1.591 | 0.256 | 0.230 |
| On-demand vehicle | Intercept | 2.234 | 0.060 | −1.171 | 0.092 |
|                    | Gender | −0.984 | 0.127 | 0.374 | −0.352 | 0.336 |
|                    | Age | −1.085 | 0.011 | 0.338 | 0.104 | 0.708 |
|                    | NMI | 2.145 | 0.001 | 8.854 | 1.132 | 0.001 |
|                    | Occupation | −0.207 | 0.462 | 0.813 | −0.245 | 0.126 |
|                    | Vehicle ownership | −0.718 | 0.245 | 0.488 | −0.395 | 0.317 |
|                    | Reliability | 0.884 | 0.019 | 2.420 | 0.412 | 0.112 |
|                    | Availability | −0.235 | 0.552 | 0.791 | 0.525 | 0.071 |
|                    | Cost-effectiveness | −0.514 | 0.141 | 0.598 | −0.647 | 0.003 |
| Private vehicle | Intercept | −5.235 | 0.000 | −7.430 | 0.000 |
|                    | Gender | −1.565 | 0.011 | 0.209 | −1.262 | 0.001 |
|                    | Age | −1.353 | 0.001 | 0.259 | 0.021 | 0.942 |
|                    | NMI | 2.961 | 0.001 | 7.856 | 1.479 | 0.000 |
|                    | Occupation | 0.182 | 0.488 | 1.200 | −0.159 | 0.307 |
|                    | Vehicle ownership | 3.673 | 0.000 | 39.383 | 4.342 | 0.000 |
|                    | Reliability | 1.357 | 0.000 | 3.885 | 0.473 | 0.063 |
|                    | Availability | 0.888 | 0.021 | 2.431 | 1.326 | 0.000 |
|                    | Cost-effectiveness | 0.020 | 0.952 | 1.021 | −0.190 | 0.411 |
| Public transport | Intercept | 4.823 | 0.000 | 1.401 | 0.014 |
|                    | Gender | −1.472 | 0.012 | 0.229 | −0.883 | 0.008 |
|                    | Age | −1.147 | 0.002 | 0.318 | 0.544 | 0.033 |
|                    | NMI | 1.741 | 0.004 | 5.701 | 0.383 | 0.249 |
|                    | Occupation | −0.003 | 0.991 | 0.997 | −0.261 | 0.081 |
|                    | Vehicle ownership | −1.675 | 0.003 | 0.187 | −1.056 | 0.004 |
|                    | Reliability | −0.617 | 0.077 | 0.540 | −0.630 | 0.006 |
|                    | Availability | −0.869 | 0.017 | 0.419 | −0.230 | 0.385 |
|                    | Cost-effectiveness | 1.171 | 0.000 | 3.224 | 0.353 | 0.708 |
| Walk | Intercept | −1.997 | 0.119 | −3.459 | 0.000 |
|                    | Gender | −1.562 | 0.016 | 0.210 | −0.429 | 0.309 |
|                    | Age | −0.969 | 0.020 | 0.379 | 0.610 | 0.048 |
|                    | NMI | 1.490 | 0.020 | 4.436 | 0.444 | 0.265 |
|                    | Occupation | 0.274 | 0.321 | 1.316 | −0.041 | 0.825 |
|                    | Vehicle ownership | −0.677 | 0.276 | 0.508 | −1.098 | 0.028 |
|                    | Reliability | 0.229 | 0.557 | 1.257 | 0.073 | 0.825 |
|                    | Availability | 0.413 | 0.328 | 1.511 | 0.244 | 0.535 |
|                    | Cost-effectiveness | 1.081 | 0.004 | 2.948 | 0.566 | 0.059 |

Table 5
Classification of observed and predicted values before COVID-19 commute activity trips.

| Observed | Predicted |
|----------|-----------|
| No Trip | Non-motorized Vehicle (Rickshaw/Cycle) | On demand Vehicle (UBER/Pathao/CNG/Taxi) | Private Vehicle (Car/Bike) | Public Transport (Bus/Leguna) | Walk | Percent Correct |
| No Trip | 8 | 3 | 0 | 3 | 6 | 0 | 40.0 % |
| Non-motorized Vehicle | 2 | 31 | 4 | 34 | 28 | 1 | 31.0 % |
| On demand Vehicle | 1 | 7 | 9 | 12 | 14 | 0 | 20.9 % |
| Private Vehicle | 0 | 5 | 1 | 183 | 5 | 0 | 94.3 % |
| Public Transport | 1 | 15 | 4 | 6 | 145 | 0 | 84.8 % |
| Walk | 0 | 12 | 0 | 12 | 11 | 8 | 18.6 % |
| Overall Percentage | 2.1 % | 12.8 % | 3.2 % | 43.8 % | 36.6 % | 1.6 | 67.3 % |
Dhaka (Hasanat-E-Rabbi et al., 2021; Manik Saha, 2013; Pervaz et al., 2016). In addition, it needs to be mentioned that footpaths in Dhaka are mostly occupied by hawkers which increases human congestion on the provided pedestrian lane (Debnath et al., 2021). To encourage the enthusiastic pedestrians to maintain their walking behavior these hawkers should be moved somewhere else. Building of additional marketplace for the hawkers would be a viable solution. Also increasing the width of the walkway without disrupting the roadway width could be a solution to maintain recommended social distances during the pandemic.

Following the investigation, the increased mode found for both purposes was NMV. As Dhaka observes tremendous traffic congestion mostly on the busy streets of the city, it would be irrational to provide dedicated NMV lanes on those streets. Instead, transport planners should investigate the possibilities for alternate dedicated pathways for NMV on the busiest roads. Another significant shift of mode was observed towards on-demand vehicles for both purposes. Several provisions like regulations for wearing facemasks of both passengers and drivers while traveling, the use of MFS for payment should be imposed on this mode to ensure safety precautions are achieved.

This section concludes with the recommended policy implementing measures to assist the authority in planning a sustainable transportation system to deal with global crises.

6. Conclusions

This research aims to investigate the change in mode choice behavior of the residents of Dhaka due to the COVID-19 pandemic. The main focus was to assess the impact of such a pandemic on the daily commute as well as discretionary travel patterns using data extracted from the online questionnaire survey from 1st April 2021 to 15th June 2021 (10 weeks). Using 571 responses which are carefully screened, the change in primary mode use for both commute and discretionary trips was observed along with inertia analyses of overall mode preferences using Sankey diagrams. While the use of public transport has dropped, there is a jump in walking activity for discretionary purposes. In addition, on-demand vehicle usage for commuting soared during the pandemic. During the COVID-19 crisis, NMV is the only category of mode to increase its usage for both purposes. A large proportion of public transport usage has been shifted to on-demand vehicles for both purposes. Several features of the primary modes were perceived by the respondents and analyzed how the perception changed due to the crisis. Public transport is the least reliable mode in the pandemic and NMV is the most cost-effective mode for commute trips. The availability of the on-demand vehicles also jumped in this pandemic for discretionary trips. Finally, MNL model was applied to determine the influence of socio-demographic attributes and characteristics of modes on mode choice behavior. The model depicts older people were more likely to make no trip at all rather than making trips on-demand vehicles. Availability’ for before and ‘gender’ for during the pandemic is the only significant predictor in choosing modes in discretionary activity trips. It has been found that people with high income are more likely to choose on-demand vehicles in both situations and particularly for discretionary trips people were likely to use more on-demand vehicles if they were more available before COVID-19. In addition, females are less likely to choose public transport irrespective of the situation for discretionary trips and females are more likely to be uninterested in discretionary activities than to choose on-demand vehicles for discretionary trips. The MNL model predicted 67.3 % and 55 % of the cases correctly for before and during COVID-19 trips for commute activity and 68.7 % and 61.6 % of the cases for before and during COVID-19 trips for discretionary activity.

This study consists of a few limitations. The online questionnaire survey for data collection bears a possibility of inaccurate responses (Buchanan and Hvizdak, 2009), though every data set of the survey

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**Table 6**

Classification of observed and predicted values during COVID-19 commute activity trips.

| Observed | Predicted |
|----------|-----------|
| No Trip  | Non-motorized Vehicle (Rickshaw/Cycle) | On demand Vehicle (UBER/Pathao/CNG/Taxi) | Private Vehicle (Car/Bike) | Public Transport (Bus/Leguna) | Walk | Percent Correct |
| No Trip  | 38 | 10 | 5 | 10 | 24 | 1 | 43.2 % |
| Non-motorized Vehicle (Rickshaw/Cycle) | 18 | 32 | 4 | 41 | 10 | 1 | 30.2 % |
| On demand Vehicle (UBER/Pathao/CNG/Taxi) | 9 | 11 | 18 | 13 | 10 | 1 | 29.0 % |
| Private Vehicle (Car/Bike) | 8 | 6 | 1 | 166 | 1 | 0 | 91.2 % |
| Public Transport (Bus/Leguna) | 18 | 9 | 4 | 7 | 59 | 0 | 60.8 % |
| Walk | 6 | 14 | 1 | 3 | 8 | 4 | 11.1 % |
| Overall Percentage | 17.0 | 14.4 % | 5.8 % | 42.0 % | 19.6 % | 1.2 % | 55.5 % |

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**Table 7**

Model fitting information, Goodness-of-fit, and the Pseudo R-Square for discretionary activity trip.

| Model | Model Fitting Criteria | Likelihood Ratio Tests |
|-------|------------------------|-----------------------|
|       | –2 Log-Likelihood | Chi-Square | df | Sig. |
| Before COVID-19 | Intercept Only | 1472.172 | 552.209 | 40 | 0.000 |
|       | Final | 919.963 | 2738.263 | 1865 | 0.000 |
|       | Pearson | 832.785 | 1865 | 1.000 |
|       | Deviance | 0.698 | 0.732 | 0.389 |
| During COVID-19 | Intercept Only | 1589.189 | 478.818 | 40 | 0.000 |
|       | Final | 1110.371 | 2084.691 | 1855 | 0.000 |
|       | Pearson | 995.628 | 1855 | 1.000 |
|       | Deviance | 0.648 | 0.671 | 0.310 |
result was screened twice as the best way to ensure the accuracy of a data file is to proofread the original data against the computerized data file in the data window (Tabachnick and Fidell, 2007). Moreover, travel characteristics information was collected on a limited scale in this survey. Combining the survey data with passive data (e.g. mobile phone records, or GPS tracking) may give a better representation of the travel behavior of the respondents. During model development, the necessity of attributing crisp values of the variables is time consuming and the

| Mode of transport | Independent variables | Before-COVID | During-COVID |
|-------------------|-----------------------|-------------|--------------|
|                   | Estimate | Sig. | Exp.(B) | Estimate | Sig. | Exp.(B) |
| Non-motorized vehicle | Intercept | 1.092 | 0.440 | -2.046 | 0.012 |
|                    | Gender | -0.855 | 0.271 | 0.425 | -0.815 | 0.047 | 0.443 |
|                    | Age | 0.055 | 0.921 | 1.056 | -0.157 | 0.607 | 0.854 |
|                    | NMI | 1.419 | 0.215 | 4.135 | -0.483 | 0.200 | 0.617 |
|                    | Occupation | -0.221 | 0.588 | 0.802 | -0.250 | 0.176 | 0.779 |
|                    | Vehicle Ownership | -1.263 | 0.110 | 0.283 | -0.372 | 0.403 | 0.689 |
|                    | Reliability | -0.033 | 0.949 | 0.967 | 0.059 | 0.041 | 1.914 |
|                    | Availability | 1.421 | 0.015 | 4.142 | 0.640 | 0.070 | 1.896 |
|                    | Cost-effectiveness | 0.086 | 0.862 | 1.090 | 0.198 | 0.482 | 1.219 |

| Mode of transport | Independent variables | Before-COVID | During-COVID |
|-------------------|-----------------------|-------------|--------------|
|                   | Estimate | Sig. | Exp.(B) | Estimate | Sig. | Exp.(B) |
| On-demand vehicle | Intercept | 1.026 | 0.415 | -0.696 | 0.024 |
|                    | Gender | -1.025 | 0.164 | 0.359 | -0.774 | 0.024 | 0.461 |
|                    | Age | -0.160 | 0.760 | 0.852 | -0.205 | 0.422 | 0.814 |
|                    | NMI | 2.043 | 0.067 | 7.713 | 0.211 | 0.471 | 1.235 |
|                    | Occupation | -0.094 | 0.809 | 0.910 | -0.042 | 0.761 | 0.959 |
|                    | Vehicle ownership | -0.932 | 0.199 | 0.394 | -0.418 | 0.259 | 0.656 |
|                    | Reliability | 0.421 | 0.384 | 1.523 | 1.214 | 0.000 | 3.367 |
|                    | Availability | 1.186 | 0.026 | 3.272 | 0.545 | 0.052 | 1.725 |
|                    | Cost-effectiveness | -0.637 | 0.172 | 0.529 | -0.775 | 0.000 | 0.461 |

| Mode of transport | Independent variables | Before-COVID | During-COVID |
|-------------------|-----------------------|-------------|--------------|
|                   | Estimate | Sig. | Exp.(B) | Estimate | Sig. | Exp.(B) |
| Private vehicle   | Intercept | -3.409 | 0.012 | -4.585 | 0.000 |
|                    | Gender | -0.920 | 0.222 | 0.399 | -0.988 | 0.018 | 0.408 |
|                    | Age | -0.596 | 0.269 | 0.551 | -0.727 | 0.012 | 0.483 |
|                    | NMI | 2.227 | 0.047 | 9.271 | 0.332 | 0.285 | 1.394 |
|                    | Occupation | -0.123 | 0.755 | 0.884 | -0.087 | 0.554 | 0.917 |
|                    | Vehicle ownership | 2.865 | 0.000 | 17.555 | 3.582 | 0.000 | 35.933 |
|                    | Reliability | 0.301 | 0.540 | 1.352 | 1.070 | 0.000 | 2.914 |
|                    | Availability | 1.313 | 0.016 | 3.718 | 0.814 | 0.009 | 2.257 |
|                    | Cost-effectiveness | 0.271 | 0.569 | 1.312 | -0.195 | 0.405 | 0.823 |

| Mode of transport | Independent variables | Before-COVID | During-COVID |
|-------------------|-----------------------|-------------|--------------|
| Public transport  | Intercept | 2.014 | 0.107 | 0.502 | 0.422 |
|                    | Gender | -1.741 | 0.020 | 0.175 | -1.313 | 0.001 | 0.269 |
|                    | Age | -0.265 | 0.618 | 0.767 | -0.087 | 0.752 | 0.917 |
|                    | NMI | 1.827 | 0.104 | 6.216 | 0.035 | 0.914 | 1.035 |
|                    | Occupation | 0.257 | 0.515 | 1.293 | 0.190 | 0.196 | 1.209 |
|                    | Vehicle ownership | -0.668 | 0.362 | 0.513 | 0.034 | 0.931 | 1.035 |
|                    | Reliability | -0.775 | 0.115 | 0.461 | 0.421 | 0.106 | 1.524 |
|                    | Availability | 0.073 | 0.894 | 1.075 | -0.467 | 0.120 | 0.627 |
|                    | Cost-effectiveness | 1.029 | 0.032 | 2.799 | 0.123 | 0.607 | 1.131 |

| Mode of transport | Independent variables | Before-COVID | During-COVID |
|-------------------|-----------------------|-------------|--------------|
| Walk              | Intercept | -3.802 | 0.059 | -3.636 | 0.002 |
|                    | Gender | -1.036 | 0.294 | 0.355 | -0.976 | 0.087 | 0.377 |
|                    | Age | -0.867 | 0.219 | 0.420 | -0.794 | 0.056 | 0.452 |
|                    | NMI | 2.134 | 0.082 | 8.451 | 0.371 | 0.407 | 1.450 |
|                    | Occupation | 0.058 | 0.902 | 1.060 | 0.217 | 0.347 | 1.242 |
|                    | Vehicle ownership | 0.622 | 0.535 | 1.862 | -0.089 | 0.883 | 0.915 |
|                    | Reliability | -0.618 | 0.317 | 0.539 | 0.820 | 0.051 | 2.269 |
|                    | Availability | 0.392 | 0.569 | 1.481 | -0.460 | 0.335 | 0.631 |
|                    | Cost-effectiveness | 1.870 | 0.007 | 6.487 | 1.108 | 0.007 | 3.027 |

Table 9
Classification of observed and predicted values before COVID-19 discretionary activity trips.

| Observed          | Predicted          |
|-------------------|--------------------|
| Non-motorized Vehicle (Rickshaw/Cycle) | 5 | 29 | 10 | 5 | 0 | 10.2 % |
| Not interested    | 0 | 1 | 6 | 1 | 2 | 0 | 10.0 % |
| On demand Vehicle (UBER/Pathao/CNG/Taxi) | 0 | 0 | 132 | 39 | 22 | 0 | 68.4 % |
| Private Vehicle (Car/Bike) | 0 | 0 | 13 | 177 | 5 | 0 | 90.8 % |
| Public Transport (Bus/Leguna) | 2 | 0 | 21 | 14 | 77 | 0 | 67.5 % |
| Walk              | 0 | 0 | 2 | 5 | 3 | 0 | 0.0 % |
| Overall Percentage | 1.2 % | 0.2 % | 35.6 % | 43.1 % | 20.0 % | 0 | 68.7 % |
variables should be measured accurately. On top of that, human approximations are not promptly captured by the MNL model (Pulugurta et al., 2013). Furthermore, the present study was confined to only Dhaka City; the inclusion of responses from rural areas may show a change in the significance level and parameter estimate of the variables.

Collaboration of researchers from all over the world along with local and global policymakers is necessary to bring impactful results. This article suggests copious future research insights to focus on the preparedness to deal with future pandemics. Researchers could compare the mode choice behavioral pattern of consecutive waves of the current pandemic or may analyze the in-depth analysis of travel behavior due to starting the vaccination program to validate the more manifested result. Moreover, this study could be viable for comparing the results from the studies in cities with similar socio-demographic characteristics. Advanced machine learning techniques to develop models can be a direction of future research.

CRediT authorship contribution statement

**Tonmoy Paul:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing.

**Rohit Chakraborty:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing.

**Salma Afia Ratri:** Methodology, Writing – original draft, Writing – review & editing.

**Mithun Debnath:** Supervision, Writing – review & editing, Resources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Al-Salih, W.Q., Ezstergari-Kins, D., 2021. Linking mode choice with travel behavior by using logit model based on utility function. Sustainability (Switzerland) 13 (8). https://doi.org/10.3390/su13084332.

Anwari, N., et al., 2021. ‘Exploring the travel behavior changes caused by the COVID-19 crisis: A case study for a developing country’, Transportation Research Interdisciplinary Perspectives, Perspectives 9 (March). https://doi.org/10.1016/j.trip.2021.100354.

Ben-Akiva, M. and Lerman, S. (1985) ‘Discrete Choice Analysis: Theory and Application to Travel Demand’, in.

Bhaduri, E., et al., 2020. Modelling the effects of COVID-19 on travel mode choice behaviour in India. Transport. Res. Interdiscip. Perspect. 8 (December), 100273 https://doi.org/10.1016/j.trtp.2020.100273.

Bin, E., et al., 2021. The trade-off behaviours between virtual and physical activities during the first wave of the COVID-19 pandemic period. European Transport Research Review 13 (1). https://doi.org/10.1186/s12544-021-00473-7.

Buchanan, E.A., Hvizdak, E.E., 2009. Online survey tools: Ethical and methodological concerns of human research ethics committees. Journal of Empirical Research on Human Research Ethics 4 (2), 27-48. https://doi.org/10.1525/jer.2009.4.2.27.

Carozzi, F., Provenzano, S. and Roth, S. (2020) ‘Urban Density and COVID-19 ‐ CORONAVIRUS DISEASE 2019 (COVID-19)’, European Transport Research Review 13 (1). https://doi.org/10.1186/s12544-021-00473-7.

Chowdhury, T., Paul et al. (2021). ‘Classification of observed and predicted values before COVID-19 discretionary activity trips.’ Transportation Research Interdisciplinary Perspectives 15 (2022) 100665.

Debnath, M., et al., 2021. An investigation of urban pedestrian behaviour in Bangladesh using the Perceptual Cycle Model. Saf. Sci. 138, 105214 https://doi.org/10.1016/j.ssci.2021.105214.

Dhaka Tribune (2021) ‘Bengal enviro'lution: Are you satisfied with travelling during the pandemic?’ Dhaka Tribune. https://doi.org/10.32866/001c.17977.

Eisenmann, C., et al., 2021. Transportation mode use during the COVID-19 lockdown period in Germany: The car became more important, public transport lost ground. Transp. Policy 103 (January), 60-67. https://doi.org/10.1016/j.tranpol.2021.01.012.

Esrar, M. I. (1992) HOME-BASED TRIP GENERATION MODELLING FOR DHAKA CITY. Bangladesh University of Science and Technology.

Guoyuan, X.Y., Hu, Q.J., 2020. Analysis of second outbreak of COVID-19 after relaxation of control measures in India. Nonlinear Dyn. https://doi.org/10.1007/s11071-020-05989-6.

Hasanat-E-Rabbi, M., Hamim, M., Faisal, Md. Shamsul, Rich C., McIlroy, Katherine L., Plant, Neville A., Stanton, 2021. Exploring the Relationships between Demographics, Road Safety Attitudes, and Self-Reported Pedestrian Behaviours in Bangladesh. Sustainability 15 (8). https://doi.org/10.3390/su15084332.

Hossain, M., et al., 2021. ‘Exploring the travel behavior changes caused by the COVID-19 crisis: A case study for a developing country’, Transportation Research Interdisciplinary Perspectives, Perspectives 9 (March). https://doi.org/10.1016/j.trip.2021.100354.

IDLC (2017) Ride- Sharing in Bangladesh : Disrupting the way we commute, Monthly Business Review.

Islam, A., et al., 2021. Geospatial dynamics of COVID-19 clusters and hotspots in Bangladesh. Transboundary Emerg. Diseases. https://doi.org/10.1111/1758-2687.13249.

Jamal, S., Paez, A., 2020. Changes in trip-making frequency by mode during COVID-19. Transp. Res. Rec. 2239 (1), 74-83. https://doi.org/10.3141/2239-09.

Khaddar, S., Fatmi, M.R., 2021. ‘COVID-19: Are you satisfied with traveling during the pandemic?’ Dhaka Tribune. https://doi.org/10.32866/001c.17977.

Kemp, S. (2021) ‘Do you believe that the public will still travel by plane’, Business Review.

Kemp, S. (2021) ’Are you satisfied with traveling after the first wave of the COVID-19 pandemic?’, Business Review.

Khan, S., Bhiyani, A.A., 2021. New Window Opens for Digital Advancement. Global J. Manage. Business Res.: G Interdisp. 21 (1), 21–35.

Lee, D., Derrible, S. and Pereira, F. C. (2018) ‘Comparison of Four Types of Artificial Neural Network and a Multinomial Logit Model for Travel Mode Choice Modelling’. doi:10.1177/0306198118796971.

Luan, S., et al., 2021. Exploring the impact of COVID-19 on individual’s travel mode choice in China. Transp. Policy 106 (March), 271–280. https://doi.org/10.1016/j.tranpol.2021.04.011.
