Identifying the Changes in Mode Choice Behavior Due to COVID-19 in Dhaka Metropolitan Area

by

Mustafa Fardin

Md. Bulbul Islam

A thesis submitted to the

Department of Civil Engineering

in partial fulfillment for the degree of

BACHELOR OF SCIENCE IN CIVIL ENGINEERING

Department of Civil Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh

May 2022

ACKNOWLEDGEMENTS

To begin with, we would like to express our sincere gratitude to our thesis advisor, Dr. Md. Mizanur Rahman, for providing us with continuous advice and encouragement as we conducted this study and prepared our dissertation. His effort to our group can only be recognized, never compensated. His consistent motivation encouraged us to complete this thesis project with diligence and added to our abilities to approach and solve any problems. Without his consistent direction, this dissertation would not have been completed.

We owe our family and friends gratitude for their support and encouragement. We are most grateful to Almighty Allah for His boundless blessings in our lives.

In conclusion, we would like to thank our department, the respected members of my examination board, Dr. Moazzem Hossain, and our supervisor, Dr. Md. Mizanur Rahman, once again for providing us with this opportunity, which has unquestionably greatly increased our knowledge and skills as students of civil engineering.

ABSTRACT

Various measures, recommended or imposed by the Government of Bangladesh to control the spread of COVID-19, impacted the travel behavior of the urban travelers significantly. Showcasing high impacts while the lockdowns in place, similar research suggested that the effects of such will impact mode choice behavior significantly in a period after lockdowns as people blend in with new normalcy. This study aimed at examining the changes that occurred in travel and mode choice behavior after the repealing of lockdowns and models the change in the factors that affect mode choice. Data were collected through an online questionnaire survey, limited to Dhaka Metropolitan Area and dispersed through social media ad campaign, which included questions on trip purpose, mode choice, distance traveled, and frequency of trips before and after COVID-19 lockdowns. Two hundred and ninety-five responses were collected from the survey which were analyzed through non-parametric and parametric analysis to compare between pre-lockdown and post-lockdown periods.

Results explained that trip purpose, mode choice, cost of trip, frequency of trips and importance imparted on various Levels of Service (LOS) factors for the primary travel were significantly different before and after the lockdown. There was a significant shift from public transport to private transport and non-motorized modes while people placed a higher priority on the pandemic related concerns while choosing a mode during the pandemic as compared to the general concerns or trip attributes. Importance imparted on various vehicle characteristics, trip attributes and safety related attributes shifted significantly as travelers preferred shorter distance, shorter time and cost-efficient modes in pre-lockdown time, while preferring safer, higher cost, less distance and crowding to be more important factors in the new normal situation. Significant changes in factors affecting mode choice were observed, as household income, employment status and safety & distancing in vehicle impacted travelers to shift from public transport to private vehicles and non-motorized vehicles. Government authorities could utilize such knowledge for planning smart and partial lockdowns in the event of future lockdowns and also, utilize the knowledge in making the new public transportation systems to match users' needs.

Keywords: COVID-19 Pandemic, Travel Behavior, Mode Choice Modelling, Multinomial Logit Models, Interaction Variables and Analysis

TABLE OF CONTENT

ABSTRACT iii

LIST OF FIGURES vii

LIST OF TABLES viii

CHAPTER 1 1

INTRODUCTION 1

1.1 Overview 1
1.2 Overall Transport Scenario during COVID-19 1
1.3 Motivation of the Research 3
1.4 Research Objectives 5
1.5 Scope & Outcomes 5
1.6 Organization of the thesis 6

CHAPTER 2 7

Literature Review 7

2.1 Introduction 7
2.2 Disaggregate Mode Choice Analysis 7
2.3 Individual Mode Choice Behavior and Decision Rule 7
2.4 Discrete Choice Theory 8
2.5 Probabilistic Choice Theory 9
2.6 Factors Influencing the Choice of Mode 9
2.7 Previous research on mode selection in the context of COVID 19 pandemic 11
2.8 Random Utility Theory 14
2.9 Random Utility Models 15
2.10 Logistic Regression Model 15
2.10.1 Explanatory variables: 16
2.10.2 Outcome variables: 17
2.10.3 Multinomial Logistic Regression: 17
2.11 Wilcoxon Signed Rank Test 19
2.11.1 Test Procedure 19
2.11.2 Computing the null distribution 20
2.12 McNemar's test 23
2.12.1 Definition 23
2.12.2 Variations 24
2.13 Exploratory factor analysis 25
2.13.1 Fitting procedures 26
2.13.2 Maximum likelihood 26
2.13.3 Principal axis factoring 27
2.13.4 Factor Structure (Sphericity and KMO) 27

2.14 Models for Dhaka City's Mode Choice 27
CHAPTER 3 31
Methodology 31
3.1 Introduction 31
3.2 Methodology Overview 31
3.3 Literature Review 32
3.4 Concept Development and Formulation of Objectives 32
3.5 Survey Design 32
3.6 Data Collection 34
3.7 Data Preparation 35
3.7.1 Data Preparation for Descriptive Analysis 36
3.7.2 Data Preparation for Exploratory Factor Analysis 36
3.7.3 Data Preparation for Calibration of Multinomial Logit Model 37
3.8 Data Analysis 39
3.8.1 Descriptive Analysis 39
3.8.2 Exploratory Factor Analysis 40
3.8.3 Estimation Multinomial Logit Model 41
3.9 Comparative Analysis Between Models 41
3.10 Summary 45
CHAPTER 4 46
Changes in Travel and Mode Choice Behavior 46
4.1 Introduction 46
4.2 Socio-economic demographics of the respondents 46
4.3 Shift in Mode Choice by Socio-Demographic Characteristics 48
4.3.1 Gender 48
4.3.2 Age 48
4.3.3 Income 50
4.3.4 Education 51
4.3.5 Occupation 53
4.3.6 Type Of Residence 55
4.3.7 Place Owning 57
4.4 Factors Affecting the Mode Choice Decision of the travelers 57
4.5 Shift in Travel Purpose Before and After Lockdown 60
4.6 Non-commuting Trip Frequency 62
4.7 Preferred Modes 62
CHAPTER 5 64
Modeling Mode Choice and Analysis 64
5.1 Introduction 64
5.2 Available Modes 64
5.3 Dimensionality Reduction for High Correlation 65
5.3.1 Exploratory Factor Analysis (EFA) 67
5.4 Rationale for Selection of Variables/Hypothesis 68
5.4.1 Statistical Significance 70
5.4.2 Goodness of Fit Statistics 70
5.4.3 Interpretation of Parameter Estimates 71
5.5 Mode Choice Model Before Lockdowns 71
5.5.1 Model Specification 71

5.5.2 Interpretation of Parameter Estimates 74
5.6 Mode Choice Model After Lockdowns 75
5.6.1 Model Specification 76
5.6.2 Interpretation of Parameter Estimates 78
5.7 Comparative Analysis of Interaction Between Pre and Post Lockdown Models 80
5.7.1 Model Specification 80
5.7.2 Interpretation of Parameter Estimates 83
5.8 Summary 87
CHAPTER 6 88
Results and Discussion 88
6.1 Introduction 88
6.2 Changes in the Travel & Mode Choice Behavior 88
6.2.1 Modal Shift 88
6.2.2 Trip Characteristics 90
6.2.3 Importance Imparted on Various Levels of Service (LOS) and Trip Characteristics 92
6.3 Changes in the Impact of Mode Choice Factors 94
6.4 Discussion 97
6.4.1 Private Vehicles (PV) in Post-Lockdown 97
6.4.2 Non-Motorized Vehicles (NMV) in Post-Lockdown 100
6.5 Summary 103
CHAPTER 7 104
Conclusions and Future Works 104
7.1 Concluding Remarks 104
7.2 Research Contribution 105
7.3 Recommendation 106
7.4 Limitations & Future Research 106
REFERENCES 108
APPENDIX 114

LIST OF FIGURES

Figure 3-1. Overview of the Methodology. 31

Figure 4-1. Modes Used by Different Genders in Pre and Post Lockdown Setting 48

Figure 4-2. Modes Used by Different Ages in Pre and Post Lockdown Setting 49

Figure 4-3. Mode of transportation used by travelers according to their household income before and after lockdown 51

Figure 4-4. Mode of transportation used by travelers according to their education before and after lockdown 53

Figure 4-5. Mode of transportation used by travelers according to their occupation before and after lockdown 55

Figure 4-6. Mode of transportation used by travelers according to their type of residence before and after lockdown 56

Figure 4-7. Mode of transportation used by travelers according to place owning before lockdown 57

Figure 4-8. Distribution of responses for the factors influencing mode preferences before lockdown 58

Figure 4-9. Distribution of responses for the factors influencing mode preferences after lockdown. 59

Figure 4-10. Before and after lockdown, shift in the primary purpose of travel (results of McNemar test) 61

Figure 4-11. Mode shift due to COVID-19 (results of McNemar test). 62

Figure 5-1. Correlation Matrix of pre-Lockdown variables 65

Figure 5-2. Correlation Matrix of post-Lockdown variables 66

Figure 5-3. Scree Plot of the two Data 67

Figure 6-1. Vehicle Composition in Before and After Lockdown Setting 89

Figure 6-2. Weekly Trip Frequency in Pre and Post Lockdown Setting 91

Figure 6-3. Change in Average Importance Imparted on Various Attributes in Pre and Post Lockdown Setting 92

LIST OF TABLES

Table 2-1. Example of Contingency Table Tabulating Outcome of Two Tests 23

Table 4-1. Summary of the Socio-Demographic Status of Respondents.....47

Table 4-2. Importance of different factors affecting the mode choice of the travelers before lockdown.....57

Table 4-3: Importance of different factors affecting the mode choice of the travelers after lockdown 58

Table 5-1. Modes Used in the Models 65

Table 5-2. Outputs of KMO and Bartlett's Test of Sphericity for EFA 66

Table 5-3. Summary of the Latent Factors for Pre-Lockdown Variables.....67

Table 5-4. Summary of the Latent Factors for Post-Lockdown Variables 68

Table 5-5. List of Variables Used in the Models 69

Table 5-6. Goodness of Fit Measures of Pre-Lockdown Model.....72

Table 5-7. Estimation of Coefficients, the Statistically Significant Level, Odds Ratio and Confidence Interval of Odds Ratios of the Variables of the Multinomial Logit Model in Pre-Lockdown Setting for Private Vehicles.....72

Table 5-8. Estimation of Coefficients, the Statistically Significant Level, Odds Ratio and Confidence Interval of Odds Ratios of the Variables of the Multinomial Logit Model in Pre-Lockdown Setting for Non-Motorized Vehicles 73

Table 5-9. Goodness of Fit Measures of Post-Lockdown Model 77

Table 5-10. Estimation of Coefficients, the Statistically Significant Level, Odds Ratio and Confidence Interval of Odds Ratios of the Variables of the Multinomial Logit Model in Post-Lockdown Setting for Private Vehicles 77

Table 5-11. Estimation of Coefficients, the Statistically Significant Level, Odds Ratio and Confidence Interval of Odds Ratios of the Variables of the Multinomial Logit Model in Post-Lockdown Setting for Non-Motorized Vehicles.....78

Table 5-12. Goodness of Fit Measures of the Interaction Model 82

Table 5-13. Estimation of Coefficients, the Statistically Significance Level of the interaction model for Private Vehicles (PV).....82

Table 5-14. Estimation of Coefficients, the Statistically Significance Level of the interaction model for Non-Motorized Vehicle 83

Table 5-15. Qualitative Change in Slope in Variables Between Pre and Post Lockdown Situations for Private Vehicle (PV) 84

Table 5-16. Qualitative Change in Slope in Variables Between Pre and Post Lockdown Situations for Non-Motorized Vehicle (NMV).....86

Table 6-1. Summary of the Intermodal Shift Analysis by McNemar Test.....89

Table 6-2. Summary of Average of Trip Characteristics in Pre and Post Setting 90

Table 6-3. Summary of Average of Trip Characteristics in Pre and Post Setting 92

Table 6-4. Summary of the Impacts and Changes in Impacts of the Variables for Choosing Private Vehicle (PV) Over Public Transport (PT).....94

Table 6-5. Summary of the Impacts and Changes in Impacts of the Variables for Choosing Non-Motorized Vehicle (NMV) Over Public Transport (PT).....96

INTRODUCTION

1.1 Overview

Since early 2020, the breakout of the COVID-19 pandemic has had a profound effect on not only the Bangladesh population but also the world. Mobility was impacted significantly as the Government of Bangladesh (GOB) enforced restrictions such as lockdowns, remote work, and subsequent closing of public locations. Additionally, people attempted to limit their movements and social contacts in order to minimize the possibility of contagion. Public transportation was especially hard hit by the epidemic since passengers regarded it as dangerous and a probable source of infection (Aloi et al., 2020).

1.2 Overall Transport Scenario during COVID-19

Transport modalities are crucial platforms for the fast transmission of infection in densely populated and mixed-use metropolitan areas. This aspect is evident in the contemporary context, where people commute daily (on average 2.5 journeys per day), covering an average distance of approximately 30 kilometers, for a variety of reasons (e.g., work, study, shopping, and entertainment), using a variety of modes of transport, including foot, bicycle, public transportation, and personal vehicle (Campisi et al., 2019). Because of such, it was no surprise that the countries around the world suspended both external and internal transportation through the enactment of lockdowns (Tian et al., 2020) after the virus was declared a global pandemic on March 11, 2020 (WHO, 2020). In addition, many nations initiated various efforts to limit or halt the spread of COVID-19 in early and mid-March, including identifying travel restrictions as a compulsory countermeasure (Zhang et al., 2021).

Following the WHO guidelines and the limitations enforced by other countries, on January 22, 2020, the authorities at the Dhaka airport put the airports on alert by screening travelers from China. On March 8, 2020, the first three coronavirus cases were confirmed, subsequently leading to the government declaring a lockdown throughout the nation from March 23 to May 30 and focused on developing strategies

to stop the spread of the virus and thus, remove the citizens from harm. Following three different waves and extending lockdowns, till now (May 1, 2022), the populace has faced 1,952,674 cases of infection and 29,127 deaths till the total lifting of lockdowns for industrial and commercial operations occurred on August 11, 2021, and subsequently, the opening of educational institutions on February 22, 2022 (New Age Bangladesh, 2022). Public transportation services resumed on June 1, 2020, under some restrictions. Service providers were permitted to transport people at half their seating capacity. To compensate for revenue losses associated with decreased passenger numbers, they were permitted to charge 2/3rds more than pre-COVID-19 fares. On September 1 2020, the passenger limitation was repealed, and ticket fares were reverted to regular levels. (The Daily Star, 2020). The typical urban mobility patterns have since been rejuvenated despite the instilled mask mandate; however, the extent of the incurred impact in the new normalcy is yet unknown in the context of Bangladesh.

Globally, the transportation industry has been impacted, including air, rail, road, and water transportation. Due to the complicated supply and demand dynamics, passenger and freight transportation have also been significantly disrupted. By the end of March 2020, global road transport activity would be about 50% below the 2019 average, and commercial air activity would be nearly 75% below the 2019 normal by mid-April 2020 (IEA, 2020). Looking at a more local perspective, the UK's limits on public transportation have resulted in a 95% decline in underground travels in London. Shared bikes saw a rise in mode share for people living in Thessaloniki, Greece. In contrast, the average trip duration in New York, Chicago, and Boston has been increased together with reduction in bike trips due to COVID-19. People's travel behaviors have altered because to the fear of COVID-19 spreading and the associated regulations and prohibitions. The difference is more noticeable in travel mode choice. Initial reports and study findings indicate that passengers considered public transportation as hazardous throughout the pandemic, resulting to decreased patronage than pre-COVID-19. Transport planners are concerned about the global fall in public transport utilization and modal share. After the lockdown period, some public transport users would migrate to private modes (cars and motorbikes), which will hinder sustainable transportation results. Since the COVID-19 epidemic, there is limited indication that individuals are using active transportation more. To avoid the growth of private modal shares, measures should be taken to re-engage those who left public transport owing to the epidemic. Otherwise, local environmental issues and worldwide

CO2 emissions may worsen. Furthermore, it would be ideal if some of the normal private mode passengers switched to active modes.(M. Abdullah et al., 2020; Abu-Rayash & Dincer, 2020; Arellana et al., 2020; Aydin et al., 2022; Baig et al., 2022; Beck & Hensher, 2020; Bhaduri et al., 2020; de Vos, 2020; Marsden & Docherty, 2021; Nikiforiadis et al., 2020; Ozbilen et al., 2021; Padmanabhan et al., 2021; Pawar et al., 2020; Shakibaei et al., 2021).

In the context of Dhaka, Bangladesh, there has been significant drop in public transport usage amid COVID-19 infection waves. Various organizations and institutions shifted their operations to online structure, leading to less work/education-related trips. During the lockdowns, similar to the changes in neighboring countries & globally, there have been less use of public transport and more patronage of private motorized vehicles. Due to higher disposable income, the total number of private vehicles have increased substantially in the period leading to change in mobility patterns, specifically motorized two-wheelers (Bangladesh Road Transport Authority, 2022). Preferences for public transits (buses, Legunas, railways, etc.) decreased as well, while a rise in active transport modes were observed. In more recent lights of the new normalcy, walking and cycling was found to be more preferred. Currently, commuters have to choose between health concerns, price, and the availability of alternate forms of transport while also lacking confidence about maintaining physical distancing in public transport. As such, a dilemma exists to balance between affordability, trip characteristics and health concerns. Thus, a better understanding of how the health concerns impact their mode choice behavior in the new normal situation is necessitated to understand patterns of the future and what the focus of future policies and emerging modes should be (Md. S. Abdullah et al., 2021; Jamal et al., 2022a, 2022b; Jamal & Paez, 2020; Paul et al., 2021; Shaik et al., 2021; Zafri et al., 2021).

1.3 Motivation of the Research

Within the parts of travel demand forecasting models, i.e., four step model, mode choice arguably the most important determinant of number of vehicles on roadways (Koppelman & Bhat, 2006). However, mode selection is a more readily affected travel decision than other trip-planning considerations such as route selection or destination selection. Thus, throughout time, mode choice models have addressed the broad range of trade-offs that individuals are prepared to make between the various Levels of

Service (LOS) attributes of alternate modes. (Enam, 2010; Iseki & Taylor, 2010; Koppelman & Wen, 2000; Yasmin, 2008)

However, COVID-19, being more than a health catastrophe, impacted economics, travel, civil freedoms, and a variety of other social constructs, introduced a new dimension in the process. The transportation industry, like many other companies and industries, has been adversely impacted by this epidemic. Numerous nations, including Bangladesh, had imposed restrictions on public transit, compelling citizens to reassess their mode of transportation. In comparison to motorized modes, active means of transport such as cycling and walking have greater health advantages due to the physical activity involved, which saw an increase in use. As the concern for affordability rose in the new normal, the commuters need to balance between their concern for health, Levels of Service (LOS) and affordability. In pre-COVID times, the factors affecting mode choice of the commuters of Dhaka City depended on commuters' socio-economic characteristics and LOS attributes, however, the recent studies showcase the paradigm has shifted greatly due to COVID-19 as health concern emerged as a greater factor than before (Enam & Choudhury, 2011; Jamal et al., 2022a). As a result, for successful planning and development of the upcoming urban transportation systems of Dhaka, it is necessary to understand how the pandemic altered mode choice behavior along with the quantification of the paradigm shift in the balance between factors. Using this information, decision makers can make policies regarding facilities to be provided.

As COVID-19 is edging on being an endemic soon, along with the new normalcy, the current situation in Dhaka Megacity is different than during-COVID state. Furthermore, with the introduction of new transit services, i.e., Mass Rapid Transit (MRT) and Bus Rapid Transit (BRT), the decision makers need to consider the new state of behavior of commuters and what facilities are required to mitigate their new form of necessity. As there is already a decline in public transport, these services will need to balance between the LOS attributes and safety attributes. Existing literature and models do not account for this new state and the shift in attitude.

Therefore, the current research proposes a novel method that integrates socio-demographic, LOS and safety dimensions to mode choice decision and thus, identify the share of importance that these dimensions inhabit to create the new balance.

1.4 Research Objectives

The overall objective of this research is to understand the impacts of COVID-19 on mode choice behavior before and after COVID-19 lockdowns in Dhaka Metropolitan Area using advanced discrete choice modelling techniques that takes the attitude of the travelers towards health & safety concerns of modes in the respective time periods into consideration as well. The study comprehensively captures the change in preference for the modes available to the travelers, along with their change in attitude towards different factors that act as determinant for their choice of mode for their most frequented modes in the new normal. Specific objectives of the study include:

i) To identify the factors that are likely to affect mode choice behavior in a post-COVID setting and the shift in attitude towards such factors

ii) To develop mode choice models for identifying change in mode choice behavior between before lockdown and after lockdown periods

1.5 Scope & Outcomes

The research will examine the new paradigm for the elements that influence commuters' utility when it comes to mode selection. The models may be used to validate various mode availability scenarios, and the results of the study can be utilized to forecast future demand. With several transportation system megaprojects either underway or planned in the Dhaka Metropolitan Area, the examination of mode choice behavior has significant policy and planning implications. The study's findings offer potential interventions (modification of fee structure, expansion of service, and reduction of trip time) for building a well-integrated public transportation system and minimizing reliance on automobiles. Additionally, it can provide light on the development of non-motorized vehicle and active transportation systems in order to facilitate the integration of heavy systems. Taking into account the varying travel patterns of various groups of users, decision makers may make the best choice possible in order to minimize reliance on vehicles and increase the percentage of passengers who utilize public transit.

This section should specify the main objective of the research. Scopes, central ideas and contributions are also included. Several questions should also be answered in this section. What will and what will not be included? What is new/better/significant?

The research objectives with specific aims and expected outcomes of the research should also be presented in this section. You may use bullet points to list the specific aims and expected outcomes.

1.6 Organization of the thesis

This section should have a brief description of the thesis outline of thesis. It should contain the chapter no. with title and brief descriptions of the content of each chapter. An example guide is provided below.

Chapter 1: Introduction and Objective. This chapter provides the background and motivations of the research. The overall objectives and expected outcomes are also described in this chapter.

Chapter 2: Literature Review. This chapter reviews the related works in the field of mode choice modelling with a special focus on COVID-19

Chapter 3: Methodology. This chapter describes the methodology adopted to carry out the research.

Chapter 4: Changes in Travel and Mode Choice Behavior. This chapter focuses on identifying the changes from the collected data, corresponding to pre and post lockdown and check whether the changes are significant

Chapter 5: Modelling Mode Choice and Analysis. This chapter models the mode choice in pre and post lockdown setting and compares between the two to interpret change in impact of factors

Chapter 6: Results and Discussion. This chapter describes the results of the research and discusses the results with baselines.

Chapter 7: Conclusions and Future Work. This chapter summarizes the conclusions and major contributions of this study and provides recommendations for policy makers and future stides.

Literature Review

2.1 Introduction

The past studies and reports on mode choice analysis are presented in this chapter. This literature review will aid in the completion of our study's objective by identifying the scope of work that will be undertaken for this thesis work. Once again, this chapter provides a historical overview of a diverse range of modeling approaches that have been developed and are currently in use.

2.2 Disaggregate Mode Choice Analysis

Mode choice studies can be roughly classified into aggregate and disaggregate approaches. The aggregate technique directly estimates the modal split using data collected at the zonal or group level. Rather than representing the behavior of a single passenger, aggregated models seek to describe the average behavior of a group of travelers. However, despite its degree of closeness, the group may not be completely homogeneous. As a consequence of pre-estimation data aggregation, the models lose accuracy. As a consequence, such models' reliability and validity have always been called into doubt) (Ben-Akiva, 1985). On the other hand, disaggregate mode choice modeling provides a number of significant benefits over aggregate mode choice modeling. It captures the unique behavior of passengers. Individual mode selection behavior and decision rule are critical in disaggregate modeling. As a consequence, it can account for changes in choosing behavior as a result of changes in individual characteristics and alternative features (Koppelman F. S., 2006). The behavioral aspect of disaggregate models and their associated accuracy have resulted in disaggregate models being widely used in mode choice analysis.

2.3 Individual Mode Choice Behavior and Decision Rule

The individual traveler is the decision-making unit in a disaggregated approach. A necessary condition for modeling mode selection is that the model is directed by the passengers' behavioral principles. In other words, it should exemplify the choice made

by passengers when faced with other options. Travelers' mode of transportation choice is the result of a sequential decision-making process (Ben-Akiva, 1985). The decision problem is defined as the first phase in the procedure. This is determined by the trip's context; for instance, the method of transportation used to go to work. Following that, the passenger must choose an other form of transport. The mode of transport considered by the traveler is heavily influenced by the modes' availability, the passengers' cost, and informational restrictions, among other factors. The passenger must next weigh the advantages and disadvantages of the competing modes (for example, time, cost, comfort, and convenience). The traveler must use the choice rule in order to choose amongst various modes after considering their qualities. The decision rule is critical since it establishes the final selection. Even though the list of options is same and the attribute values are identical, the choice made by each decision rule might be different. The decision theory literature investigates a broad range of choice rules (Tversky, 1972). Rule dominance, rule of satisfaction, lexicographic rule, and utility maximization rule are four types of mode selection decision rules. A mode is dominant over another if it is better for at least one characteristic and not worse for all other qualities, according to the rule of dominance. According to the rule of satisfaction, an option may be rejected if it does not satisfy the condition for at least one characteristic. Both of these criteria, however, have the constraint of not providing the decision maker with a unique option. The third rule is the lexicographic rule, which states that the decision maker will pick the option that is most appealing in terms of the most critical feature. The utility of a mode is represented as a function of the combination of its qualities according to the utility maximization criterion (for example, travel time, cost, comfort etc.). The passenger will choose for the most convenient form of transport. Among all of these decision rules, the most frequently utilized is the utility maximization rule, which simulates the passengers' rational decision-making (Ben-Akiva, 1985).

2.4 Discrete Choice Theory

Discrete choice theory is a significant invention in the field of transportation planning for analyzing and forecasting passengers' individual mode selection behavior. The idea derives from microeconomic consumer choice theory (Lancaster, 1966), which is based on utility maximization. In discrete choice, a discrete collection of possibilities is studied rather than a continuous range of alternatives. These distinct

possibilities are mutually exclusive and exhaustive together, and the traveler must make just one decision (Ben-Akiva, 1985). By and large, discrete choice analysis is based on the maximizing of utility. As such, the traveler is required to choose the mode that provides the most benefit among competing modes.

2.5 Probabilistic Choice Theory

It is not always feasible to see and quantify all of the variables influencing human decision-making. As a consequence, choice experiments are almost always connected with inconsistencies of some kind. To begin, observations are inherently inconsistent, and secondly, human preference is non-transitive (Ben-Akiva, 1985). Even under identical option situations, a single passenger may not repeatedly pick the same mode. Additionally, individuals with similar decision sets, socioeconomic status, and preferences may not choose the same method of transportation Such discrepancies in human behavior are addressed by probabilistic choice theory. This notion originated in the realm of psychology (Luce, 1965). The probabilistic approach to decision mechanisms allows for the consideration of unobserved variation in choice makers and unobserved features of alternatives.It accounts for the unpredictability inherent in human behavior and the mistakes caused by unobserved variance.

2.6 Factors Influencing the Choice of Mode

There are a variety of elements that influence the mode of transportation that travelers choose to use. There are three types of characteristics: characteristics of the trip maker, characteristics of the route, and characteristics of transport facilities. The socio-demographic variables such as age, gender, income, car ownership, family structure, and so on, are the most important characteristics of the trip makers to consider. According to several research, gender is one of the most critical elements influencing mode selection. According to research, female travelers are more likely than male tourists to use public transportation (Polk, 2004). The age of the passenger is also taken into consideration while selecting a form of transportation. According to (Morikawa, 2003), older individuals are more inclined to use public transportation, while younger people prefer to drive their own automobiles or private vehicles. In addition, (Limtanakool, 2006) discovered a statistically significant relationship between age and mode choice. Both income and automobile ownership influence the

socio-economic status of passengers and, as a result, their choice of mode of transportation while traveling. Travelers with a high income and vehicle ownership are more likely to pick a car for regular travel, while persons with a low income are more likely to use public transportation for regular travel (Abuhamoud, 2011). (Limtanakool, 2006) discovered that high-income people prefer faster modes of transportation that have a higher cost of transportation.

The objective, intricacy, and duration of the trip all impact mode choice. This is due of the regularity and flexibility of the travel to work. In this case, too, the distance traveled is a factor. Inter-city travel is distinct from inter-city travel. A lengthier travel distance is normally required for the latter. The function of public transportation is always dominating for suburban commuters and inter-urban travelers (Wardman, 2000).Tour complexity and trip chaining pattern impact mode choice significantly, according to (Ye, 2007)

Travel time (in vehicle, out vehicle, waiting time), travel cost, availability, and dependability are all characteristics of transport facilities. Travel time and cost directly influence utility and mode selection. Various studies demonstrate that transportation fares directly affect transit ridership (Sharaby, 2012). Travel time is very vital for tourists. More travel time means less chance of commuters picking a mode. However, the time implications vary by modality. Traveling by bus or vehicle takes longer than walking or bicycling. Similarly, OVT is more sensitive than IVT (Koppelman, 2006). Transit ridership may be affected by the reliability of public transportation. Unexpected delays in public transit are called unreliability (Yatskiv, 2012). Regularity of journey time, adherence to schedule, and arrival (Janos, 2002) .Reliability is vital for luring passengers to public transit, according to many studies (Bates, 2001).

Most early studies on mode choice simply included mode-specific characteristics like time, cost, distance and socio-demographic factors like age, gender, income. Convenience and safety are crucial attitudinal aspects that should be included in mode selection research. Crowding and seating effect public transportation choices. The problem of safety and security is also raised by transit users in several research (Iseki, 2009). Individual decision-making is aided by these elements (McFadden, 1986). Different research have indicated that combining attitude and psychological elements with typical objective decision qualities like time and money improves the model's explanatory power and hence better reflects reality (Kuppam, 1999).

2.7 Previous research on mode selection in the context of COVID 19 pandemic

(Matthew J. Beck, 2020) reported preliminary findings from a survey conducted in mid-March 2020, during Australia's first (and possibly only) COVID-19 pandemic epidemic and gathered subsequent waves of data to ascertain what changes in travel behavior in particular might persist in the short term, if not longer. The data collected during the peak of the COVID-19 restrictions would be extremely informative. They made 93 proposals across seven sectors: agriculture and freight, aviation, public transportation, motor vehicles and road use, active transportation, flexible employment, and infrastructure investment. The survey covered a broad range of actions and attitudes, allowing us to convey the nation's mood regarding the COVID-19 threat, the response to the pandemic, and the disruption of travel and activities.

(Muhammad AbdullahNazam Ali, 2021) demonstrated the COVID-19 epidemic's impact on travel patterns and mode choices in three cities in Pakistan's Punjab region. An online survey was used following the pandemic to collect data on demographics and factors influencing modes of travel previously to and during the epidemic. Statistical study found differences in travel intentions between pre- and post-pandemic periods. The data indicated that fewer people traveled for work or education than usual during the pandemic. Individuals traveled more for shopping throughout the pandemic. The number of trips made for non-commuting purposes prior to and following the pandemic was found to be significantly different. Males made more non-commuting trips than females during the outbreak. Over 30s and automobile owners took significantly more non-commuting excursions. Prior to and during the epidemic, non-commuting travel was associated with a positive relationship between monthly household income and non-commuting travel.

(Banerjee, 2021) discusses the possibility of a shift from public transportation to driving as a result of the coronavirus epidemic, potential reasons influencing the mode shift, and appropriate tactics for boosting public transportation use in the future world. The results of a logistic regression model based on an online questionnaire survey done in India reveal that commuters' socioeconomic attributes such as age, gender, and monthly income have a substantial effect on mode switch preferences. Additionally, trip features such as journey time, crowded, and hygiene are substantially associated with a preference for driving versus public transportation. Additionally, commuters'

impressions of numerous public transportation promotion tactics were analyzed, which will pave the way for the creation of post-COVID transportation policies.

(Sogbe, 2021) attempts to collect data from 1005 commuters via an online and paper-based questionnaire that included questions about their preferred mode of transportation, preferred mode of public transportation prior to and during the COVID-19 period, and factors influencing their preferred mode of public transportation prior to and during the COVID-19 period. Statistical analysis comprised both descriptive and comparative quantitative analysis. Inferential statistical analysis was performed using non-parametric tests. To determine if the conventional method of transportation has changed as a result of COVID-19, the Wilcoxon signed-ranked test was employed to compare factors impacting mode choice prior to and during the implementation of COVID-19.

(Kramberger, 2021) concentrated on the changes in travel habits of Vienna residents as a result of the infection. The same research on spatial modeling commuters' mode of transport choice in Vienna was finished in 2019 and is a continuation of our prior work. According to our created technique, this article demonstrates that public transportation is no longer the primary means of transport as it was before to the viral outbreak. The primary outcome of this work is a map of modal shift in Vienna with geographically defined areas of applicability for specific options, which may give theoretical support for policymakers and transportation planners.

In the United States, the effects of COVID-19 on transportation service and passenger traffic are lasting longer than anticipated (Parker, 2021) .The COVID-19 pandemic's impact on individual travel behavior across the United States was examined. From January to December 2020, we studied mobility data from a sample taken from a countrywide smartphone-based panel curated by a private firm, Embee Mobile, as well as a survey administered to that group in August 2020. This analysis sheds light on travel patterns and the immediate impact on transport riders of the COVID-19 pandemic.

(Haghshenas, 2021) While we did a study to examine changes in the elderly's active mode of transport (walking and cycling) as a result of the COVID-19 outbreak crisis, no research has been conducted on the elderly's active mode choice during the COVID-19 epidemic. The data from a structured questionnaire were analyzed using a binary logistic regression model. The primary factors influencing the elderly's active trip mode selection are trip distance and vehicle ownership, trip frequency, bicycle ownership, the

quality of walking and cycling routes, intersection safety, neighborhood security and greenery, traffic calming, CBD accommodation, and public transportation accessibility.

(Abdullah, 2020) investigates the changes in travel behavior that happened as a result of the COVID19 epidemic. The data were obtained via an online questionnaire survey that included questions about the purpose of the trip, the form of transportation used, the distance traveled, and the frequency of travels prior to and during COVID19. 1203 replies were gathered from a variety of nations worldwide. The findings indicated that prior to and during the pandemic, trip purpose, method of travel, distance traveled, and frequency of trips for principal travel were significantly different. Additionally, the bulk of travels made during the pandemic were for shopping. There was a considerable shift away from public transportation and toward private and nonmotorized modes of transport. When picking a mode during a pandemic, people prioritized pandemic-related worries over general issues. Gender, car ownership, employment status, trip distance, primary purpose of travel, and pandemic-related underlying characteristics were revealed to be significant predictors of mode choice during COVID19. The findings of this study may be valuable in transportation planning and policymaking during pandemics, as they will be based on people's travel demands.

(Kamplimath, 2021) discovered that travel frequency is decreasing and that the style of travel in the 'New Normal' will be determined by safety and hygiene. Additionally, respondents are willing to pay a premium for improved transportation services. If the government does not address these concerns, users' preference for public transportation will decline significantly. Additionally, travel frequency will decline significantly, resulting in a greater disparity between travel demand and supply. In the future, statistical modeling and machine learning technologies will be utilized to evaluate the findings and forecast future changes in the travel behavior of long-distance travelers.

To ascertain the influence of this unique disease on individual travel behavior and mobility patterns, an online poll was undertaken across India's metropolitan agglomerations (Thombre, 2021). The objective is to document travel mode selections before to, during, and after scenarios. Additionally, the study seeks to elicit answers in favor of a more secure and disaster-resilient public transportation system that can also accommodate the needs of private vehicle owners. Additionally, the study proposes and assesses a series of medium- to long-term policy prescriptions for mitigating the crisis's

consequences and capitalizing on the opportunity it has created to realize the long-held ambition of sustainable and resilient cities in the context of urban mobility.

(Zafri, 2021) examines the anticipated shift in active transportation mode usage in Bangladesh's new normal circumstance using data from a questionnaire survey. According to the poll, 56% and 45% of respondents, respectively, projected to increase their walking and bike travel during the new normal condition. On the other side, 19% of respondents were predicted to act in the opposite manner. Additionally, the study develops multinomial logistic regression models to identify the factors impacting the projected change in travel by active transport modes under the new normal condition. Finally, this study makes policy recommendations for expanding active transportation use beyond the pandemic and ensuring sustainable mobility for city people and their health.

(Bari, 2021) makes an attempt to determine the influence of COVID-19 on traffic patterns and students' mode of transportation to their host institute. The response survey was conducted, and the participants' pre- and post-travel habits were examined. The intriguing conclusion is that regardless of financial level, parents are more concerned about their child's safety from COVID-19. Due to the inadequacy of the infrastructure to implement the COVID-19 protocol, parents have insisted on sending their children to school via their personalized mode, subject to the strictest social distance norms enforced by schools. Policymakers and planners can utilize the findings from this study to determine the effect of educational excursions.

2.8 Random Utility Theory

It was McFadden who laid the theoretical foundation for Random Utility Theory, as previously indicated (1974a, 1974b). Manski's seminal work in 1977, Manski and Mcfadden's seminal work in 1981, and Ben-Akiva and Lerman's landmark work in 1993 were all important contributions (1985). If you use a random utility technique to analyze choice behavior, the observed inconsistencies in choice behavior are viewed as the analyst's observational weakness, which may be caused by unobserved taste variation, unobserved characteristics, measurement error, and the use of proxy variables (Manski, 1973). It is always believed that the person would choose the option that provides the most utility. The analyst considers the utility of the user to be a random variable that is unknown to him or her. The choice probability of an alternative i is

equal to the probability that the utility of alternative i, U_{in}, is greater than or equal to the utilities of all other alternatives in the choice set. This can be written as follows:

$$P(\, i \mid C_n \,) = P(U_{in} \;\geq\; U_{jn}, all\; j \in C_n$$

According to probabilistic choice theory, the genuine utility is represented by qualities that have been seen and those that have not been observed. One component of the utility function indicates the fraction of the utility that can be seen by the analyst, which is referred to as the deterministic (or observable) portion of the utility (V_{in}) in most cases. Due to the fact that the other component is unknown, it is represented as a random error (ε_{in}).

$$U_{in} = V_{in} + \varepsilon_{in}$$
$$P(\, i \mid C_n \,) = P(V_{in} + \varepsilon_{in} \;\geq\; V_{jn} + \varepsilon_{jn}, all\; j \in C_n$$
$$P(\, i \mid C_n \,) = P(\varepsilon_{jn} - \varepsilon_{in} \;\leq\; V_{in} - \; V_{jn}, all\; j \in C_n$$

2.9 Random Utility Models

Different Random Utility Models have been developed, each of which is based on a different assumption about the distribution of the random component of the utility function (the random part of the utility function). It is assumed in logit models that the random part of the utility is distributed in an independently and identically distributed (IID) extreme value, and it is assumed in nested logit models that the random part of the utility is distributed in an independently and identically distributed (IID) generalized extreme value (GEV). In the Probit model, on the other hand, it is assumed that the distribution is a multivariate normal distribution. Logit, on the other hand, is computationally simpler and more interpretable. As a result, the logit model is by far the most extensively used discrete choice model in the world (Train, 2009).

2.10 Logistic Regression Model

It is a statistical model in statistics that models the probability of one event (out of two alternatives) taking place by assuming that the log-odds (the logarithm of the odds) for the event are derived from a linear combination of one or more independent variables. In statistics, the (binary) logistic model (also known as the logit model) is one of the most commonly used models ("predictors"). Logistic regression (also known as logit regression) is a kind of regression analysis that estimates the parameters of a logistic model (the coefficients in the linear combination). In terms of formulating a model, binary logistic regression has just two values: "0" and "1." The dependent

variable is a single binary variable, coded by an indicator variable, with the two values labeled "0" and "1," and the independent variables can either be binary variables (with two classes, coded by an indicator variable) or continuous variables (any real value). Since the corresponding probability of the value labeled "1" might vary between 0 and 1 (definitely the value "0"), the logistic function is named after the function that transforms log-odds to probability. The unit of measurement for the log-odds scale is called a logit, which is derived from the term logistic unit, which explains the several other names.

The basic setup of logistic regression is as follows. Given a dataset of N points, we must get the mean of the points in the dataset. In each point, there is a set of independent variables $x_{1,i}...x_{m,i}$ (also known as predictor variables, features, or attributes) and a binary outcome variable Y_i (also known as a dependent variable, response variable, output variable, or class), which can only take on the two possible values 0 (often meaning "no" or "failure") or 1 (often meaning "yes" or "success" in the situation (often meaning "yes" or "success"). The purpose of logistic regression is to utilize a dataset to develop a predictive model of an outcome variable that can be predicted.

As in linear regression, the result variables Y_i are supposed to be dependent on the explanatory factors $x_{1,i}... x_{m,i}$, where I is the number of explanatory variables.

2.10.1 Explanatory variables:

They may be of any kind, including real-valued, binary, category and other types of variables. In mathematics, the most important difference is between continuous and discrete variables.

The use of dummy variables (or indicator variables) to code discrete variables with more than two possible values is common practice; that is, separate explanatory variables with the values 0 or 1 are created for each possible value of the discrete variable, with a 1 indicating that the variable has the given value and a 0 indicating that the variable does not have that value.

2.10.2 Outcome variables:

To put it another way, the outcomes Y_i are characterized as Bernoulli-distributed data, in which each result is decided by an unobserved probability pi that is individual to the outcome at hand, but is connected to the explanatory factors in some way. Alternatively, any of the following comparable expressions may be used to represent this: value".)

$$Y_i|x_{1,i}, \dots, x_{m,i} \sim Bernoulli(p_i)$$

$$\varepsilon\left[Y_i\middle|x_{1,i}, \dots, x_{m,i}\right] = p_i$$

$$\Pr(Y_i = y \mid x_{1,i}, \dots, x_{m,i}) = \begin{cases} p_i & if\ y = 1 \\ 1 - p_i & if\ y = 0 \end{cases}$$

$$\Pr(Y_i = y \mid x_{1,i}, \dots, x_{m,i}) = p_i^y (1 - p_i)^{(1-y)}$$

2.10.3 Multinomial Logistic Regression:

The probability that the outcome was in category 1 was given by p(x) and the probability that the outcome was in category 0 was given by 1-p(x). The total of both probability is equal to one, as it must be, since they are both equal to one.

If we have M+1 explanatory variables (including x_0) and N+1 categories, we will need to create N+1 separate probability distributions, one for each category and indexed by n. These probability distributions will describe the probability that the categorical outcome y for explanatory vector x will be in category y=n for the explanatory vector x. As a result, it will be needed that the total of these probabilities across all categories equals one. This probability, calculated in the mathematically handy base e, are as follows:

$$p_n(x) = \frac{e^{\beta_n . x}}{1 + \sum_{u-1}^{N} e^{\beta_n . x}}\ for\ n = 1,2, \dots, N$$

$$p_0(x) = 1 - \sum_{n=1}^{N} p_n(x) = \frac{1}{1 + \sum_{u-1}^{N} e^{\beta_n . x}}$$

The regression coefficients n for each probability, with the exception of $p_o(x)$, will be unique to that probability. It can be observed that the total of the $p_n(x)$ across all

categories equals unity, as needed. It should be noted that the choice of po(x) as the probability to be described in terms of the other probabilities was arbitrary. Any one of the probability may have been chosen to be defined in this way. "Pivot index" is the particular value of n that is used in this calculation. The log-odds (t_n) are calculated in terms of the pivot probability, which is then stated as a linear combination of the explanatory variables:

$$t_n = \ln\left(\frac{p_n(x)}{p_n(x)}\right) = \beta_n \cdot x$$

It is now possible to determine the log-likelihood that a certain set of K measurements or data points will be obtained as a result of the probabilities stated above. Let the k-th set of measured explanatory variables be represented by x_k, and their categorical outcomes be indicated by y_k, where y_k may be any integer in the range [0,N]. The log-likelihood is then

$$\iota = \sum_{k=1}^{K}\sum_{n=0}^{N} \Delta(n, y_k)\ln\left(p_n(x_k)\right)$$

the value of which is equal to unity if y_k=n and zero otherwise, and the indicator function $\Delta(n,y_k)$ With two explanatory variables, this indicator function was defined as y_k when n = 1 and 1-y_k when n = 0. When n = 0, this indicator function was defined as y_k. This was handy, but it was not required. Again, finding the optimal beta coefficients may be accomplished by maximizing the log-likelihood function, which can be accomplished using numerical approaches in most cases. Setting the derivatives of the log-likelihood with respect to each beta coefficient equal to zero and then solving for the beta coefficients is one technique of solving for the beta coefficients.

$$\frac{\partial l}{\partial \beta_{nm}} = 0 = \sum_{k=1}^{K} \Delta(n, y_k)x_{mk} - \sum_{k=1}^{K} p_n(x_k)x_{mk}$$

Where β_{nm} is the *m*-th coefficient of the β_n vector and x_{mk} is the *m*-th explanatory variable of the *k*-th measurement. Once the beta coefficients have been estimated from the data, we will be able to estimate the probability that any subsequent set of explanatory variables will result in any of the possible outcome categories. (contributors, Logistic regression, 2022)

2.11 Wilcoxon Signed Rank Test

The Wilcoxon signed-rank test is a non-parametric statistical hypothesis test used either to test the location of a population based on a sample of data, or to compare the locations of two populations using two matched samples. The one-sample version serves a purpose similar to that of the one-sample Student's *t*-test. For two matched samples, it is a paired difference test like the paired Student's *t*-test (also known as the "*t*-test for matched pairs" or "*t*-test for dependent samples"). The Wilcoxon test can be a good alternative to the *t*-test when population means are not of interest; for example, when one wishes to test whether a population's median is nonzero, or whether there is a better than 50% chance that a sample from one population is greater than a sample from another population.

2.11.1 Test Procedure

There are two variants of the signed-rank test. From a theoretical point of view, the one-sample test is more fundamental because the paired sample test is performed by converting the data to the situation of the one-sample test. However, most practical applications of the signed-rank test arise from paired data.

For a paired sample test, the data consists of samples (X_1,Y_1), ...,(X_n,Y_n) . Each sample is a pair of measurements. In the simplest case, the measurements are on an interval scale. Then they may be converted to real numbers, and the paired sample test is converted to a one-sample test by replacing each pair of numbers (X_i,Y_i) by its difference X_i-Y_i In general, it must be possible to rank the differences between the pairs. This requires that the data be on an *ordered metric* scale, a type of scale that carries more information than an ordinal scale but may have less than an interval scale.

The data for a one-sample test is a set of real number samples $X_1,\ldots..,X_n$. Assume for simplicity that the samples have distinct absolute values and that no sample equals zero. (Zeros and ties introduce several complications; see below.) The test is performed as follows:

Compute $|X_1|,\ldots.,|X_n|$.

Sort $|X_1|,\ldots.,|X_n|$, and use this sorted list to assign ranks $R_1,\ldots.,R_n$: The rank of the smallest observation is one, the rank of the next smallest is two, and so on.

Let sgn denote the sign function: $\operatorname{sgn}(x)=1$ if $x>0$ and $\operatorname{sgn}(x)=-1$ if $x<0$. The test statistic is the signed-rank sum T:

$$T = \sum_{i=1}^{N} sgn(X_i)R_i$$

Produce a p-value by comparing T to its distribution under the null hypothesis.

The ranks are defined so that R_i is the number of j for which $|X_j| \leq |X_i|$. Additionally, if $\sigma:\{1,\ldots,n\}$ is such that $|X_{\sigma(1)}| < \ldots < |X_{\sigma(n)}|$, then $R_{\sigma(i)} = I$ for all i .

The signed-rank sum T is closely related to two other test statistics. The *positive-rank sum* T^+ and the *negative-rank sum* T^- are defined by

$$T^+ = \sum_{1 \leq i \leq n, X_i > 0} R_i,$$

$$T^- = \sum_{1 \leq i \leq n, X_i < 0} R_i.$$

Because $T^+ + T^-$ equals the sum of all the ranks, which is $1+2+\ldots\ldots+n = n(n+1)/2$, these three statistics are related by:

$$T^+ = \frac{n(n+1)}{2} - T^- = \frac{n(n+1)}{4} + \frac{T}{2},$$

$$T^- = \frac{n(n+1)}{2} - T^+ = \frac{n(n+1)}{4} - \frac{T}{2},$$

$$T = T^+ - T^- = 2T^+ - \frac{n(n+1)}{2} = \frac{n(n+1)}{2} - T^-$$

Because T, T^+, and T^- carry the same information, any of them may be used as the test statistic.

The positive-rank sum and negative-rank sum have alternative interpretations that are useful for the theory behind the test. Define the *Walsh average* W_{ij} to be $\frac{1}{2}(X_i + X_j)$. Then:

$$T^+ = \{W_{ij} > 0 : 1 \leq i \leq j \leq n\},$$

$$T^+ = \{W_{ij} < 0 : 1 \leq i \leq j \leq n\}.$$

2.11.2 Computing the null distribution

Computing *p*-values requires knowing the distribution of T under the null hypothesis. There is no closed formula for this distribution. However, for small values of n , the distribution may be computed exactly. Under the null hypothesis that the data is symmetric about zero, each X_i is exactly as likely to be positive as it is negative.

Therefore the probability that T=t under the null hypothesis is equal to the number of sign combinations that yield T=t divided by the number of possible sign combinations 2^n. This can be used to compute the exact distribution of T under the null hypothesis.

Computing the distribution of T by considering all possibilities requires computing 2^n sums, which is intractable for all but the smallest n. However, there is an efficient recursion for the distribution of T Define $u_n(t^+)$ to be the number of sign combinations for which $T^+=t^+$. This is equal to the number of subsets of {1,….,n} which sum to t^+ . The base cases of the recursion are $u_o(0)$, $u_o(t^+)=0$ for all $t^+ \neq 0$, and $u_n(t^+)=0$ for all t<0 or t>n(n+1)/2. The recursive formula is

$$u_n(t^+) = u_{n-1}(t^+) + u_{n-1}(t^+ - n).$$

The formula is true because every subset of {1,…..,n} which sums to t^+ either does not contain n, in which case it is also a subset of {1,….,n-1}, or it does contain n, in which case removing n from the subset produces a subset of {1,….,n-1} which sums to t^+-n. Under the null hypothesis, the probability mass function of T^+ satisfies $Pr(T^+=t^+\}=u_n(t^+)/2^n$. The function u_n is closely related to the integer partition function.

If $p_n(t^+)$ is the probability that $T^+=t^+$ under the null hypothesis when there are n samples, then $p_n(t^+)$ satisfies a similar recursion:

$$2p_n(t^+) = p_{n-1}(t^+) + p_{n-1}(t^+ - n).$$

with similar boundary conditions. There is also a recursive formula for the cumulative distribution function $Pr(T^+ \leq t^+)$

For very large n, even the above recursion is too slow. In this case, the null distribution can be approximated. The null distributions of T, T^+, and T^- are asymptotically normal with means and variances:

$$E[T^+] = E[T^-] = \frac{n(n+1)}{4},$$

$$E[T] = 0,$$

$$Var(T^+) = Var(T^-) = \frac{n(n+1)(2n+1)}{24},$$

$$Var(T) = \frac{n(n+1)(2n+1)}{6}.$$

Better approximations can be produced using Edgeworth expansions. Using a fourth-order Edgeworth expansion shows that:

$$\Pr(T^+ \leq k) \approx \Phi(t) + \phi(t)\left(\frac{3n^2+3n-1}{10n(n+1)(2n+1)}\right)(t^3 - 3t)$$

Where,

$$t = \frac{k + \frac{1}{2} - \frac{n(n+1)}{4}}{\sqrt{\frac{n(n+1)(2n+1)}{6}}}$$

The technical underpinnings of these expansions are rather involved, because conventional Edgeworth expansions apply to sums of IID continuous random variables, while T^+ is a sum of non-identically distributed discrete random variables. The final result, however, is that the above expansion has an error of $O(n^{-3/2})$, just like a conventional fourth-order Edgeworth expansion

The moment generating function of has the exact formula:

$$M(t) = \frac{1}{2^n}\prod_{j=1}^{n}\left(1 + e^{jt}\right).$$

When zeros are present and the signed-rank zero procedure is used, or when ties are present and the average rank procedure is used, the null distribution of T changes. Cureton derived a normal approximation for this situation. Suppose that the original number of observations was n and the number of zeros was z. The tie correction is

$$c = \sum t^3 - t$$

where the sum is over all the size t of each group of tied observations. The expectation of T is still zero, while the expectation of T^+ is

$$E[T^+] = \frac{n(n+1)}{4} - \frac{z(z+1)}{4}.$$

If

$$\sigma^2 = \frac{n(n+1)(2n+1) - z(z+1)(2z+1) - c/2}{6}$$

Then

$$Var(T) = \sigma^2$$

$$Var(T^+) = \sigma^2/4,$$

(contributors, Wilcoxon signed-rank test, 2022)

2.12 McNemar's test

In statistics, McNemar's test is a statistical test used on paired nominal data. It is applied to 2 × 2 contingency tables with a dichotomous trait, with matched pairs of subjects, to determine whether the row and column marginal frequencies are equal (that is, whether there is "marginal homogeneity"). It is named after Quinn McNemar, who introduced it in 1947. An application of the test in genetics is the transmission disequilibrium test for detecting linkage disequilibrium.

The commonly used parameters to assess a diagnostic test in medical sciences are sensitivity and specificity. Sensitivity (or recall) is the ability of a test to correctly identify the people with disease. Specificity (or precision) is the ability of the test to correctly identify those without the disease.

Now presume two tests are performed on the same group of patients. And also presume that these tests have identical sensitivity and specificity. In this situation one is carried away by these findings and presume that both the tests are equivalent. However, this may not be the case. For this we have to study the patients with disease and patients without disease (by a reference test). We also have to find out where these two tests disagree with each other. This is precisely the basis of McNemar's test. This test compares the sensitivity and specificity of two diagnostic tests on the same group of patients.

2.12.1 Definition

The test is applied to a 2 × 2 contingency table, which tabulates the outcomes of two tests on a sample of *N* subjects, is exhibited in **Table 2-1**.

Table 2-1. Example of Contingency Table Tabulating Outcome of Two Tests

	Test 1 Positive	**Test 2 negative**	**Row total**
Test 1 positive	a	b	a+b
Test 2 negative	c	d	c+d
Column total	a+c	b+d	N

The null hypothesis of marginal homogeneity states that the two marginal probabilities for each outcome are the same, i.e., $p_a + p_b = p_a + p_c$ and $p_c + p_d = p_b + p_d$.

Thus, the null and alternative hypotheses are

$$H_0 : p_b = p_c$$
$$H_0 : p_b \neq p_c$$

Here p_a, etc., denote the theoretical probability of occurrences in cells with the corresponding label.

The McNemar test statistic is:

$$\chi^2 = \frac{(b-c)^2}{b+c}$$

Under the null hypothesis, with a sufficiently large number of discordant (cells b and c), has a chi-squared distribution with 1 degree of freedom. If the $\chi 2$ result is significant, this provides sufficient evidence to reject the null hypothesis, in favor of the alternative hypothesis that $p_b \neq p_c$, which would mean that the marginal proportions are significantly different from each other.

2.12.2 Variations

If either *b* or *c* is small ($b + c < 25$) then $\chi 2$is not well-approximated by the chi-squared distribution. An exact binomial test can then be used, where *b* is compared to a binomial distribution with size parameter $n = b + c$ and $p = 0.5$. Effectively, the exact binomial test evaluates the imbalance in the discordant *b* and *c*. To achieve a two-sided P-value, the P-value of the extreme tail should be multiplied by 2. For $b \geq c$:

$$exact - P - value = 2 \sum_{i=b}^{n} \binom{n}{i} 0.5^i (1-0.5)^{n-i}$$

which is simply twice the binomial distribution cumulative distribution function with $p = 0.5$ and $n = b + c$.

Edwards proposed the following continuity corrected version of the McNemar test to approximate the binomial exact-P-value:

$$\chi^2 = \frac{(|b-c|-1)^2}{b+c}$$

The mid-P McNemar test (mid-p binomial test) is calculated by subtracting half the probability of the observed *b* from the exact one-sided P-value, then double it to obtain the two-sided mid-P-value:

$$mid - p - value = 2\left(\sum_{i-b}^{n} \binom{n}{i} 0.5^i (1-0.5)^{n-i} - 0.5 \binom{n}{b} 0.5^b (1-0.5)^{n-b}\right)$$

This is equivalent to:

$$mid - p - value = exact - p - value - \binom{n}{b} 0.5^b (1 - 0.5)^{n-b}$$

where the second term is the binomial distribution probability mass function and $n = b + c$. Binomial distribution functions are readily available in common software packages and the McNemar mid-P test can easily be calculated.

The traditional advice has been to use the exact binomial test when $b + c < 25$. However, simulations have shown both the exact binomial test and the McNemar test with continuity correction to be overly conservative. When $b + c < 6$, the exact-P-value always exceeds the common significance level 0.05. The original McNemar test was most powerful, but often slightly liberal. The mid-P version was almost as powerful as the asymptotic McNemar test and was not found to exceed the nominal significance level. (contributors, McNemar's test, 2022)

2.13 Exploratory factor analysis

In multivariate statistics, exploratory factor analysis (EFA) is a statistical method used to uncover the underlying structure of a relatively large set of variables. EFA is a technique within factor analysis whose overarching goal is to identify the underlying relationships between measured variables. It is commonly used by researchers when developing a scale (a *scale* is a collection of questions used to measure a particular research topic) and serves to identify a set of latent constructs underlying a battery of measured variables. It should be used when the researcher has no *a priori* hypothesis about factors or patterns of measured variables. *Measured variables* are any one of several attributes of people that may be observed and measured. Examples of measured variables could be the physical height, weight, and pulse rate of a human being. Usually, researchers would have a large number of measured variables, which are assumed to be related to a smaller number of "unobserved" factors. Researchers must carefully consider the number of measured variables to include in the analysis. EFA procedures are more accurate when each factor is represented by multiple measured variables in the analysis.

EFA is based on the common factor model. In this model, manifest variables are expressed as a function of common factors, unique factors, and errors of measurement. Each unique factor influences only one manifest variable and does not explain

correlations between manifest variables. Common factors influence more than one manifest variable and "factor loadings" are measures of the influence of a common factor on a manifest variable. For the EFA procedure, we are more interested in identifying the common factors and the related manifest variables.

EFA assumes that any indicator/measured variable may be associated with any factor. When developing a scale, researchers should use EFA first before moving on to confirmatory factor analysis (CFA). EFA is essential to determine underlying factors/constructs for a set of measured variables; while CFA allows the researcher to test the hypothesis that a relationship between the observed variables and their underlying latent factor(s)/construct(s) exists. EFA requires the researcher to make a number of important decisions about how to conduct the analysis because there is no one set method.

2.13.1 Fitting procedures

Fitting procedures are used to estimate the factor loadings and unique variances of the model (*Factor loadings* are the regression coefficients between items and factors and measure the influence of a common factor on a measured variable). There are several factor analysis fitting methods to choose from, however there is little information on all of their strengths and weaknesses, and many don't even have an exact name that is used consistently. Principal axis factoring (PAF) and maximum likelihood (ML) are two extraction methods that are generally recommended. In general, ML or PAF give the best results, depending on whether data are normally distributed or if the assumption of normality has been violated.

2.13.2 Maximum likelihood

The maximum likelihood method has many advantages in that it allows researchers to compute of a wide range of indexes of the goodness of fit of the model, it allows researchers to test the statistical significance of factor loadings, calculate correlations among factors and compute confidence intervals for these parameters. ML is the best choice when data are normally distributed because “it allows for the computation of a wide range of indexes of the goodness of fit of the model [and] permits statistical significance testing of factor loadings and correlations among factors and the computation of confidence intervals”.

2.13.3 Principal axis factoring

It is Called “principal” axis factoring because the first factor accounts for as much common variance as possible, then the second factor next most variance, and so on. PAF is a descriptive procedure, so it is best to use when the focus is just on your sample, and you do not plan to generalize the results beyond your sample. A downside of PAF is that it provides a limited range of goodness-of-fit indexes compared to ML and does not allow for the computation of confidence intervals and significance tests. (contributors, Exploratory factor analysis, 2022)

2.13.4 Factor Structure (Sphericity and KMO)

The first step is to test if the dataset is suitable for carrying out factor analysis. There are two

Bartlett’s Test of Sphericity: This tests whether a matrix (of correlations) is significantly different from an identity matrix. The test provides probability that the correlation matrix has significant correlations among at least some of the variables in a dataset, a prerequisite for factor analysis to work. In other words, before starting with factor analysis, one needs to check whether Bartlett’s test of sphericity is significant.

Kaiser, Meyer, Olkin (KMO) Measure of Sampling Adequacy (MSA): This test was introduced by Kaiser (1970) as the Measure of Sampling Adequacy (MSA), later modified by Kaiser and Rice (1974). The Kaiser-Meyer-Olkin (KMO) statistic, which can vary from 0 to 1, indicates the degree to which each variable in a set is predicted without error by the other variables. A value of 0 indicates that the sum of partial correlations is large relative to the sum correlations, indicating factor analysis is likely to be inappropriate. A KMO value close to 1 indicates that the sum of partial correlations is not large relative to the sum of correlations and so factor analysis should yield distinct and reliable factors. (Makowski, 2018)

2.14 Models for Dhaka City's Mode Choice

Due to the fact that Dhaka is an old city, just a few mode choice models have been built for the city so far. For the most part, these mode choice studies were restricted to exploratory evaluations of variables influencing travel demand. The mode selection

models that have been created so far for Dhaka city are briefly reviewed in the section below.

(Hasan, 2007) used a semi-rule-based mode choice model to create a four-step travel demand model (Dhaka strategic transport model, DSTM). In this model, travelers having access to vehicles were supposed to always choose the car as their means of transport regardless of other criteria such as trip distance, trip purpose, or situational limitations. For the remaining travelers (i.e., those without access to a vehicle), a Multinomial Logit (MNL) model was constructed to evaluate the rickshaw, auto-rickshaw, and public transportation options.

In 2004, Louis Berger Inc. and Bangladesh Consultants Ltd. (BCL) performed a large scale household survey funded by the World Bank to gather RP data from travelers. A Strategic Transport Plan (STP, 2005) was presented, using a four-step travel demand modeling approach. Dhaka's forms of transport are classified into two categories: transit and car. The modal split model does not include non-motorized modes (rickshaws), even though they account for 37% of trips in Dhaka (STP, 2005). By default, vehicles and taxis were grouped in the auto mode, despite their highly varying operating costs, availability and accessibility. The modal split model employed just two explanatory variables, trip time and travel cost, and generated three models for three income classes in Dhaka. People earning between Taka 12,500 and Taka 55,000 per month were put together. A vehicle is available in this broad range of income, but monthly transportation costs vary significantly. This suggests that low-income individuals are more sensitive to travel time than high-income persons, which is contradictory. The mode's travel duration and cost are likewise impractical.

(Habib, 2002) also used a four-step travel demand model for Dhaka (DUTM) that used aggregate mode share data to calibrate a modal split model. The modes modelled include rickshaw, automobile, bus, and autorickshaw. DUTM employed three explanatory variables: trip time, travel cost, and comfort. The model's parameters were tuned to best reflect the reported modal shares. Travel duration, cost, and comfort were calibrated at 0.06, 0.15, and 0.21. The coefficients for trip time and travel cost were both positive. Moreover, the coefficient for comfort was bigger than time and cost, meaning that individuals are more sensitive to comfort than time and money, which is also unrealistic.

(Aftabuzzaman, 2010) developed a mode choice model for work trips in Dhaka. The major data source was a 200-person household interview survey. The multinomial logit model only included three modes: rickshaw, bus, and auto rickshaw. The model began with three trip attributes: in-vehicle travel time, out-vehicle travel time, and travel cost, and then included coefficients for travel cost/household income and out-vehicle travel time/O-D distance. The study also proposed three policy options including bus fee reduction, bus travel time reduction, and rickshaw fare rise. In all situations, bus modal share increased while rickshaw and auto rickshaw modal shares decreased. People perceive around three out-of-vehicle minutes each minute of in-vehicle time, and the rate of substitution approximates 30 Taka per hour of in-vehicle time in Dhaka.

The Greater Dhaka Metropolitan Area Integrated Transport Study (DITS, 1993) was initiated by Bangladesh with UNDP help (UNDP). The model was built using data from the Home Interview Survey, roadside Origin-Destination survey, and traffic count survey. A typical four-step modeling technique (trip generation, distribution, mode choice, and assignment) was used by DITS (1993), where the mode choice model was condensed into sequential binomial choice models. The transport market was segmented into three monthly income categories. The DITS model examined pedestrians, rickshaws, public transit (bus or tempo), and private vehicles. The O-D pairings were distributed into four modes using binomial logit models. Walking vs public transit or rickshaw, automobile versus public transport or rickshaw, and lastly rickshaw versus public transport. This basic technique is supposed to make modal judgments. Walking is treated as a distinct mode in this model. However, many people in Dhaka walk instead of using other means since they cannot afford any of them. It is thus illogical to compare walking to other motorized and nonmotorized modes. The model anticipated that 60% of trips in Dhaka would be on foot, which sounds excessive.

(Enam, 2010) analyzed passenger preference for planned BRT and Metro Rail inside Dhaka. The mode choice model used SP and RP data. The model included 22 socio-economic factors such as income, age, gender, profession, and employment. The VOT (Value of Time) of several modalities was computed and compared. Dhaka Transport Coordination Board (DTCB) performed Dhaka Urban Transport Network

with JICA. Study (DHUTS) (JICA, 2010). The shortest route distance was used to make a modal divide between walking, rickshaw, and other modes (vehicle, bus, and auto rickshaw). Second, alternative modes were classified as private automobile, bus, and auto rickshaw, with trip expenses as the only explanatory variable. However, this extended model cannot predict real behavior since it does not account for other variables that may influence mode selection.

Recently, Dhaka Transport Coordination Board (DTCB) performed a Household (HH) survey comparable to STP (DHUTS, 2010) and produced a two step mode choice model. The mode choice model's initial phase splits walking, rickshaw, and other modes (vehicle, bus, and auto rickshaw) using O-D shortest route distance as the sole explanatory variable. Other journeys were split into private vehicle, bus, and auto rickshaw trips using solely the travel expenses as explanatory variables. The mode choice factors were evaluated for various income categories. No comprehensive mode choice models for Dhaka exist yet. The models are usually built using ad-hoc rule-based decision sets. In this case, the network-derived level of service values were utilized without correction. The models also do not account for the new MRT modes, whose LOS differs greatly from the present modes. The limitations of the existing datasets inspired the present investigation. To circumvent data constraints, this study used a stated preference survey.

Methodology

3.1 Introduction

This chapter gives a detailed overview of the data used for model development and the model framework is proposed. The methodology section of this chapter is composed of six subsections: Literature Review, Concept Development and Formulation of Objectives, Survey Design, Data Collection, Data Preparation, and Data Analysis. The research procedure is chronologically outlined henceforth, following the overview.

3.2 Methodology Overview

The study started with an extensive literature review, which led to the conceptualization, followed by the formulation of objectives. A Revealed Preference (RP) online questionnaire survey was then created, piloted and finally, conducted to collect the various socio-demographic data, preferences and opinions of travelers within Dhaka Metropolitan Area.

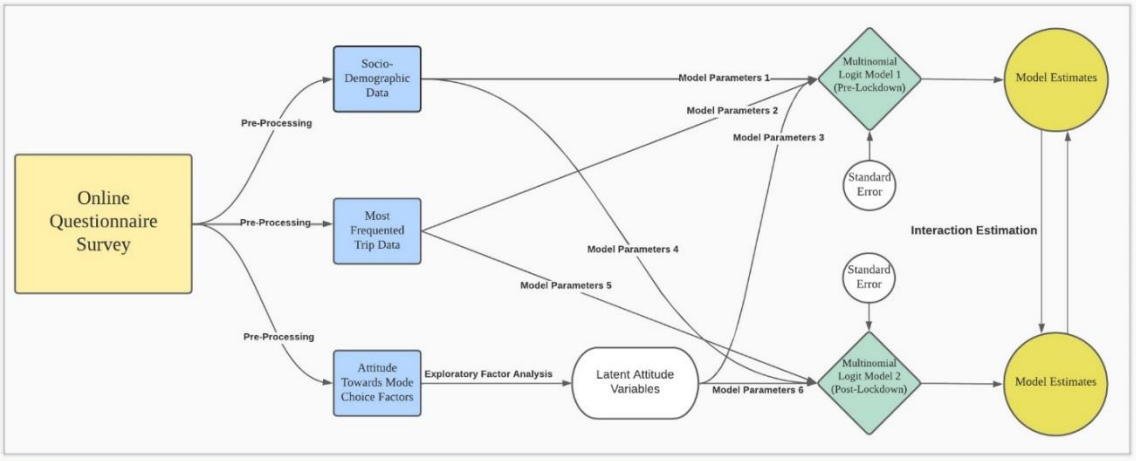


Figure 3-1. Overview of the Methodology.

The form was created in Google Forms and then distributed through a Facebook Ad Campaign. Collected data was then studied with the help of analyzing tools built in the Pandas, FactorAnalyzer, Sklearn and Statsmodels library of Python. Highly correlated

variables were reduced to latent variables by Exploratory Factor Analysis (EFA) method, which, with non-reduced observed variables were then fed into a multinomial logit model to estimate the parameters and develop two different models corresponding to the preferences before COVID-19 lockdown situation and after the removal of lockdowns. The parameters of the variables are then compared to obtain qualitative understanding of the change in their impact towards mode choice decision of the sample and thus, the model predicts their mode choice based on provided data. The models are undergone hypothesis testing, standard error calibration and goodness of fit test to understand the fit of the model and corresponding parameters. Finally, to identify whether the changes explained by the direct comparison of the models are statistically significant, an interaction model is constructed using interaction variables that explain the change in the impact of the variables from the pre-lockdown to post-lockdown model. This acts as a validatory model to understand the significance of the changes and address any heterogeneous changes that may be out of bounds of our study.

3.3 Literature Review

The first stage of the study starts with an extensive review of various relevant studies and literature, to familiarize with the theories of disaggregate travel demand model, discrete choice model with the concept of multinomial logit model and their applicability in Dhaka City and similar South-Asian developing country contexts. For literature review, the Library of the Department of Civil Engineering, and the Central Library of Bangladesh University of Engineering and Technology (BUET) have been visited. On the other hand, different journals and publications related to transportation and transport mode choice have been collected from the different web.

3.4 Concept Development and Formulation of Objectives

After a comprehensive literature review, the three overall research objectives were targeted, with expected outcomes. A basic concept of the overall data collection and processing method was constructed with consideration to the COVID-19 situation and constraints. Survey method, sample size, etc. were conceptualized as well.

3.5 Survey Design

Considering the potential of re-emergence of another COVID-19 outbreak halting data collection and to ensure the safety of both the surveyor and respondents, the whole

study was planned to be conducted online. Recent studies also found success by conducting their research surveys online, in both Bangladesh and Developing country contexts. Based on these research, Revealed Preference (RP) survey method was deemed to be most appropriate for this study. Similarly, the study area was limited to Dhaka Metropolitan Area due to the availability and exposure of travelers to online social media which are typically used for conducting online surveys in Bangladesh (see Arellana et al., 2020; Jamal et al., 2022a; Jamal & Paez, 2020; Pawar et al., 2020; Shakibaei et al., 2021). Lastly, the case study of Italy with its full lifting of lockdown akin to Bangladesh, with similar vaccination rates leading to lower chance of future lockdowns and adaptation to new normalcy, warranted the need for a before and after lockdown analysis, instead of existing literature that focuses on before and during lockdown (Torrisi et al., 2021).

Before developing the survey, the sampleable variables corresponding to the factors affecting mode choice of travelers in Dhaka Metropolitan Area was identified from relevant literature. Recommendations from previous research in relevant context were consulted for identification of the variables that may be measured from the questionnaire survey (M. Abdullah et al., 2020; Enam & Choudhury, 2011; Mogaji, 2020). Finally, 21 variables were finalized to be measured through the questionnaire survey that will provide outputs corresponding to the research objectives, which are listed in Table 4-1 along with their value labels. The period before March 23, 2020, the date of the first lockdown, was deemed as the Pre-Lockdown period and the current period starting from August 11, 2021, the date of total lifting of lockdowns, was referenced as the post-Lockdown period for comparison. Then, the questionnaire was developed using Google Forms, provided in Appendix A.

The questionnaire had three sections: (1) socio-demographic characteristics, (2) mode choices before and after COVID-19 lockdown, and (3) attitude towards factors affecting mode choice before and during COVID-19 pandemic. Socio-demographic characteristics consisted of gender, age, household size, car ownership, motorbike ownership, cycle ownership, monthly household income, employment status, type of building of residence and education level. Section 2 contained questions about their most frequented trip, mode chosen and other trip related details, i.e., cost, distance, time, etc., in before and after lockdown situations. In this study only one way trip that

is most frequented by the user from home to other locations is considered. The transport system of Dhaka city is very diverse consisting of motorized transport such as public bus, micro bus, private car, CNG, Ride-Hailing Services, taxi, human hauler, motorcycle etc. and non-motorized transport such as rickshaw, bicycle, van, walk etc. (Ahasan & Kabir, 2019). Travel and mode choice data were collected for the study on 8 alternative transport modes as listed in table 3.1. Section 3 contained 5-point Likert type items that may affect mode choice before and after COVID-19. For instance, how high a priority people place on safety, disease transmissibility, and trip distance etc. while choosing a mode. It was hypothesized that people will consider health and safety related variables to be more important while choosing a transport mode after the COVID-19 pandemic. For instance, disease transmissibility and crowding may be more important as compared to cost and distance after the pandemic. Therefore, such variables were identified and included in the questionnaire for the respondents to place a priority on each factor when choosing a transport mode. The objectives, data transparency information and instructions for filling the questionnaire were clearly described at the beginning of the questionnaire to obtain reliable data. The questionnaire was pre-tested through a pilot survey and recommendations were incorporated to ensure the clarity and understanding of each statement to the respondents.

3.6 Data Collection

Data was collected via the questionnaire survey prepared in Google Forms. Due to time and resource constraints, the study considered a sample size of travelers within Dhaka Metropolitan Area. Based on standard deviation data from a previous study (Yasmin et al., 2006) related to mode choice behavior of Dhaka residents and following a standard statistical rule (Mcgrew & Monroe, 1993) considering 95% Level of Confidence and 5% error margin, it is found that 250 can be taken as an appropriate sample size for this study. The calculation for sample size is shown below:

Sample size, $n = \left(\frac{Zs}{E}\right)^2$

$$n = \left(\frac{1.64 \times 5.18799046}{0.5379}\right)^2$$

$$n = 250$$

Where,

n = Sample Size

Z = Level of Confidence

s = Standard Deviation

E = Standard Error

To reduce sampling bias, the survey was distributed using Facebook Ad campaign restricting the locale of respondents to Dhaka Metropolitan Area. The survey contained a field of their Thana for further cross-matching. The questionnaire was available online for a period of two months from January 02 to February 26, 2022. A total of two hundred and ninety-seven (297) responses from study area were received during this period. However, due to using online surveying method, the data obtained were not devoid of selection bias, as the survey was only accessible to persons with internet access, and only those experienced with online surveys had access to participate(de Man et al., 2021). Thus, as is the case with the bulk of internet surveys, the majority of responders from this survey were young adults. As a result, this may have imposed some constraints on the study. However, based on the sample characteristics, we may conclude that we gathered a representative sample from a broad socioeconomic category and geographic area. **(Table 4-1).**

3.7 Data Preparation

This section describes the preparation of data from the travel survey as well as from the socio-economic survey databases. It addresses the major steps in acquiring, checking, and completing the data in order to prepare it to support mode choice modelling and the software used for this purpose. The study was an attempt to indicate a sensible modal choice of the urban commuters in Dhaka City in pre-lockdown and post-lockdown circumstances by calibration of multinomial model. The study also describes some generic analysis on the socio-economic, travel and attitude characteristics of the respondents. In this regard, all collected data have to be inputted and prepared for

i) Descriptive & Non-Parametric Analysis

ii) Estimation of Multinomial Logit Models and Comparative Analysis

3.7.1 Data Preparation for Descriptive Analysis

Data were prepared for the descriptive and non-parametric tests to identify significant differences between the ordinal and nominal variables, using Microsoft Excel. The survey data included a database file which contained socio-demographic, mode choice and attitude data of 297 respondents.

3.7.2 Data Preparation for Exploratory Factor Analysis

The data, received from the online questionnaire survey, was processed and encoded in Microsoft Excel for the purpose of feeding into Factor Analyzer library for Exploratory Factor Analysis (EFA). For the purpose of EFA, the attitude of the respondents towards the service and safety factors were considered, as the variables were on same scale and had high correlation among each other. The factors were then analyzed for suitability with dimensionality reduction using Kaiser-Meyer-Olkin (KMO) Test and Bartlett's Test of Sphericity, both of which concluded their suitability for EFA. Finally, the encoded attitude variables were fed into the FactorAnalyzer library of Python.

3.7.2.1 *Factors Set-Up*

The following variables, in a pre-lockdown and post-lockdown setting, were considered for the EFA and subsequent dimensionality reduction:

Importance imparted on the following factors while choosing a mode

i) *Availability of Female Seating Arrangements*
ii) *Condition of Vehicle and Seating Facilities*
iii) *Overall Vehicle and Personal Safety*
iv) *Accessibility*
v) *Crowding and Congestion*
vi) *Fear of Disease Transmissibility*
vii) *Overall Comfort*
viii) *Trip Distance*
ix) *Trip Cost*
x) *Trip Timeliness/Punctuality*
xi) *Waiting Time*

xii) Noise

xiii) Pollution

The variables were rated by the respondents on a Likert scale with the following ranges, which were coded with numerical values as shown below. Though, the Likert scale represents nominal values, as the interval between the levels are consistent and represents an increase from the lowest level to the topmost level, they could thus, be considered as continuous variable for EFA.

PreAttitude_FemaleSeating = Availability of Female Seating Arrangements before lockdowns

Not Important at All = 0
Slightly Important = 1
Moderately Important = 2
Important = 3
Very Important = 4

PostAttitude_FemaleSeating = Availability of Female Seating Arrangements after the removal of lockdowns

Not Important at All = 0
Slightly Important = 1
Moderately Important = 2
Important = 3
Very Important = 4

Where, the Pre and Post prefix denotes the period corresponding to before lockdown and after the repealing of the lockdowns. **Appendix B** outlines the encoding of all the variables for ease of comprehension and also includes the tabular form of the variables after encoding as seen in Microsoft Excel.

3.7.3 Data Preparation for Calibration of Multinomial Logit Model

At first, data input was made using Microsoft Excel for preparation of a comprehensive database for calibration of multinomial logit model. The variables were

dummy encoded using Pandas. The estimation of model was thereafter completed using Statsmodels library of Python. The accuracy was asserted using sklearn library.

3.7.3.1 *Data Set Up*

The arrangement of the data set for estimation of the multinomial logit model is described in this section, The variables considered for the estimation of multinomial logit model by using Statsmodels are:

i) Socio-Demographic Variables

- *a) Gender of the respondents*
- *b) Age of the respondents (in years)*
- *c) Education level of respondent*
- *d) Employment status of respondent*
- *e) Income range of household*
- *f) Number of Adults in respondents' household*
- *g) Number of Children in respondents' household*
- *h) Status of residence ownership*
- *i) Type of residence*
- *j) Number of Motorcycles owned by household*
- *k) Number of private cars owned by household*

ii) Mode Choice of Most Frequented Trip related variables

- *a) Number of days out in a 7-day week*
- *b) Mode used for most frequented trip in a week*
- *c) Daily use of the Mode*
- *d) Distance travelled in each trip by the mode in most frequented trip*
- *e) Cost of each one-way trip*
- *f) Travel Time of each trip*
- *g) Purpose of the trip*

iii) Reduced variables of importance imparted on service and trip factors from EFA

Numeric and descriptive types of data of above variables were collected by the questionnaire survey. The socio-demographic variables were assumed to be constant in pre and post lockdown situations for ease of comparison. But for mode choice related variables and reduced variables of importance imparted on service and trip factors, pre lockdown and post lockdown values were separately considered for two different models. As only numeric data are needed for calibration of multinomial logit mode. As a result, data with qualitative values were coded with numerical values such as 0,1, 2, …. ,6. However, for the consideration of nominal values the data were dummy encrypted, as no ordinal relationship can be established for them. The encoded variables and their label values are shown in **Appendix C.**

3.7.3.2 *Data Import to Python*

Data input of the above variables was done using Microsoft Excel and then was imported to Python using Pandas. There are thirteen variables for EFA and nineteen for each multinomial logit model without the outputs from EFA considered, in the Pandas DataFrame. There are two hundred and ninety-seven samples for each analysis.

3.8 Data Analysis

To achieve the two objectives of the study, the methodology followed three analyses for best correspondence. Starting with the descriptive and non-parametric analysis the data was cross tabulated for each mode. Successively, the importance imparted on service and trip factors while choosing mode were processed through Exploratory Factor Analysis (EFA) due to high correlation which was found from the first analysis. Lastly, the variables were used to model the mode choice of behavior of the commuters through Discrete Choice Analysis technique, and successively were fed to calibrate the multinomial logit models of pre and post lockdown situation to achieve the second objective. The detailed description of the part has been discussed in the following sections.

3.8.1 Descriptive & Non-Parametric Analysis

The analyses have been carried out through cross-tabulation, tables and charts developed by Pandas Library in Python and Microsoft Excel. This incited to get an understanding of the dataset and the varying changes of the characteristics before lockdowns and after the removal of lockdowns. How the various variables differed in

the two settings and how the changes impacted their choice of modes were also analyzed. On repeated measurements of nominal data, such as primary travel purpose prior to and during the pandemic, the McNemar-Bowker test was used. It is a nonparametric test that contains more than two levels for each nominal variable and may be expressed as a k-by-k contingency matrix. Additionally, McNemar's tests were used as post-hoc tests to deduce the levels of nominal variables that were substantially different. The McNemar test is used to determine if two matched groups vary on a binary dependent variable. To minimize type-I errors while doing multiple hypothesis tests, the Bonferroni correction was applied, which is computed as a/n, where a and n denote the significance level and number of tests, respectively. To compare ordinal repeated measurements taken under two distinct situations, such as the number of non-commuting visits made prior to and following the COVID-19 lockdowns, a non-parametric alternative to the paired t-test called the Wilcoxon signed rank test was utilized, similar to related research. (M. Abdullah et al., 2020)

3.8.2 Exploratory Factor Analysis

The questionnaire's third section contained items relating to mode preferences and the importance imparted on such. These entries correspond to a number of underlying variables. The exploratory factor analysis (EFA) approach is used to determine the underlying variables, commonly known as factors. Thus, EFA was used to ascertain the underlying factor driving mode choices during the COVID-19 epidemic. Once the underlying component was identified, factor scores were generated to indicate each respondent's relative position. In this study, regression factor scores were obtained and employed in subsequent statistical analyses. The suitability of the data was checked through Kaiser-Meyer-Olkin (KMO) Test and Bartlett's Test of Sphericity. The KMO Test measures sampling adequacy for each variable in the model and for the complete model. The statistic is a measure of the proportion of variance among variables that might be common variance. The lower the proportion, the more suited the data is to Factor Analysis. Bartlett's Test of Sphericity compares an observed correlation matrix to the identity matrix. Essentially it checks to see if there is a certain redundancy between the variables that can be summarized with a few numbers of factors. The null hypothesis of the test is that the variables are orthogonal, i.e., not correlated. The alternative hypothesis is that the variables are not orthogonal, i.e., they are correlated enough to where the correlation matrix diverges significantly from the identity matrix.

This test is often performed before employing a data reduction technique such as principal component analysis or factor analysis to verify that a data reduction technique can actually compress the data in a meaningful way. Finally, using Python's Factor Analyzer library, the factors were reduced, their loadings were measured, and the output variables were fed into the multinomial logit models.

3.8.3 Estimation Multinomial Logit Model

The most popular and widely available among different other discrete choice model is Logit Analysis. To develop the mode choice models logistic regression model has been used. However, as there are more than two alternatives of mode choice, either Nested logit or Multinomial logit model can be used. However, it is required to find which type of logit model is more appropriate to better represent the data. Logsum parameter defining the degree of association in the same nest can justify the rationale of nested logit (Ben-Akiva & Lerman, 1985). If the value of this parameter is significantly below one, it ensures similarity among the modes in the same nest. In this case, Nested logit is preferred over MNL. Otherwise, if the value is one, then it indicates no significant association among the modes in a nest (Koppelman & Bhat, 2006). In such case, assumption of Independence of Irrelevant Alternatives (IIA) is true, and NL takes the form of MNL. In this study prior to select the final model, this assumption has been tested to justify the application of more appropriate model. The logsum parameter suggested that IIA assumption is true for both models. That is why MNL is applied for modelling the mode choice.

3.9 Comparative Analysis Between Models

3.9.1.1 *Model Specification*

Model specification and further estimation of its parameters has been done in this study using Statsmodels, an open-source Python library (Seabold & Perktold, 2010). For model specification Statsmodels requires description of the parameters, specification of the utility functions, and choice of the model. For each of the model, Pre-Lockdown and Post-Lockdown, one utility function has been developed. Different explanatory variables those are proved important defining the choice of mode have been included in the models. After several trial and error, the final models has been reached.

For each of the alternative mode a utility function has been developed where the systematic part of the utility has been specified with explanatory variables. The choice of mode cannot be described entirely by the observed explanatory variables. To account the effect of unobserved factors Alternative Specific Constant (ASC) has been included. However, ASC should be included in (n-1) alternatives keeping one of the alternatives fixed (Ben-Akiva & Lerman, 1985; Koppelman & Bhat, 2006). The value of ASC was determined compared to that fixed alternative. This alternative where the value is fixed to zero for normalization acts as referent alternative. According to Ben-Akiva and Lerman (1985), it is illogical to include ASC in the utility function of each of the alternatives. In fact, all that matters is their impact on relative utility, not the absolute value. Similarly, for the same reason, socio-economic variables (income range, age, type of residence etc.) are specified in (n-1) alternatives keeping them fixed in one of the alternatives. The alternative which acts as referent alternative can be arbitrarily selected because the parameters estimated are interpreted relative to the alternative where the value is fixed to zero. In this study, for the two mode choice models of the two time period, public transports (PT) are fixed as referent alternative.

3.9.1.2 *Model Estimation*

After specification of the model, the value of the parameters specified in each utility function has been estimated by fitting the models to the observed choice data. Discrete choice analysis follows Maximum Likelihood Estimation technique for parameter estimation (Ben-Akiva & Lerman, 1985; McFadden, 1976; Train, 2001). The likelihood function for a sample of 'T' individuals, each with 'J' alternatives is defined as follows:

$$L(\beta) = \prod_{\forall \in T} \prod_{\forall \in J} (P_{jt}(\beta))^{\delta_{jt}}$$

Where,

δ_{jt} = the chosen indicator (=1 if j is chosen by individual t and, 0, otherwise)

P_{jt} = is the probability that individual t chose alternative j

3.9.1.3 *Goodness of Fit*

Log Likelihood (LL) value is an indicator of overall goodness fit of the model. Null Log likelihood, LL (0) which assumes all the parameter in the utility function is zero.

LL (β) gives the Log likelihood with the given parameters in the utility function. A higher value of LL (β) always indicates a better fit of the model. An important indicator of goodness of fit in this respect is Rho square developed by Mcfadden (McFadden, 1974). It measures the relative improvement of the model with respect to the null Log likelihood. In other words, it describes the explanatory power of the variables in the utility function for the mode choice.

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)}$$

3.9.1.4 *Statistical Tests*

Several important statistical tests have been carried out for better fit of the model. The important statistical tests those have been conducted during model estimation is briefly described below

Test of Individual Parameters

For each of the estimated parameter, t-test has been carried out which explains the significance of the parameter explaining the mode choice. The null hypothesis states that the estimated parameter has a value equal to zero. The rejection of this null hypothesis implies that the corresponding variable has a significant impact on the modal utilities and suggests that the variable should be retained in the model.

Log-likelihood Ratio Test

Log-likelihood ratio test an important test that compares two model provided that one is a restricted version of the other. Restriction can be imposed by setting one or more parameter value as zero. Thus, it allows to compare two models including or excluding the parameters to test the effect of overall fit of the model. Another application of log-likelihood ratio is to test whether a variable should be specified as generic or alternative specific. A significant test statistic indicates a better fit of the model.

The test statistic is:

$$-2 \times [LL_R - LL_U]$$

LL_R=Log-likelihood of Restricted Model

LL_U = Log-likelihood of Unrestricted Model

$$-2 \times [LL_G - LL_{AS}]$$

LL_G =Log-likelihood for the variable specified as generic

LL_U =Log-likelihood for the variable specified as alternative specific

3.9.1.5 *Comparative Interaction Analysis*

When the relationship between one predictor, X, and the outcome (response) variable, Y, depends on the value of another independent variable, Z, there is an interaction (Fisher, 1926). Z is considered to moderate the influence of X on Y, but an X Z interaction also indicates that X moderates the effect of Z on Y. Statistical interactions are sometimes referred to as moderator, modifier, qualifier, magnifier, antagonistic, effect modifier, and buffering effect. An interaction represents a synergistic or multiplicative impact investigated by adding a product variable, XZ, to the model, indicating a non-additive effect that is in addition to the linear effects of X and Y included into the model. The coefficient of regression for the product term indicates the degree of interaction between the two variables. The influence of X on Y is not the same for all values of Z, which is visually depicted by non-parallel slopes in linear regression.

If slopes are parallel, the effect of X on Y at all Z levels is the same, and there is no interaction. X and Z may be binary or continuous variables. In the scenario where both X and Z are binary, the continuous response regression model is equivalent to an analysis of variance. If the response is binary, interactions are similarly stated in logistic regression. The coefficients for the predictors X, Z, and XZ are on the right-hand side of the equation.

$$\ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta_1 X + \beta_2 Z + \beta_3 XZ$$

If the interaction coefficient β_3 is significant, we conclude that the association between X and the probability that Y = 1 depends on the values of Z. X and Z may be binary or continuous. For this study, we set Z=1 for post-lockdown time and Z=0 for pre-lockdown period, checking the hypothesis of the variable X and probability of mode change with Z. The significance of the interaction is further checked by the log likelihood of the model and a significant value of such denotes the validation of our hypothesis.

3.10 Summary

The overall methodology of the study was described in detail, with attention to the necessary framework to achieve the objectives. Various research was followed, and the findings shaped the methodology and developed the statistical techniques that were necessary. The analysis is explained in depth in the following chapters.

Changes in Travel and Mode Choice Behavior

4.1 Introduction

There are numerous factors that influence travelers' choice of mode before and after COVID 19 lockdown. The socioeconomic status of travelers, their travel behavioral patterns, and a few other significant factors all influence their mode choice. This chapter provides a detailed overview of the available factors influencing the mode choice behavior of Dhaka's travelers.

4.2 Socio-economic demographics of the respondents

Table summarizes the socioeconomic characteristics of 295 respondents whose full responses were obtained during a eight-week period. The majority of responders (74.9%) were male, aged 16–25 years (78.6 percent), and employed as students (68.8 percent). Certain groups, such as males, the young, and those with a higher level of education, comprise a greater proportion of the gathered sample, which may introduce bias into the data and derived conclusions. It should be emphasized, however, that the percentage of working women in the population is far lower owing to cultural and religious restraints. As a result, the proportion of female responses is a decent reflection of the female population, whose travel behavior was almost certainly affected by the epidemic. Similarly, the larger proportion of young and highly educated respondents may reflect that young and educated individuals are more active on social media than less educated and older respondents, i.e., those aged 46–55 years (0.7 percent) and those aged over 56 years (more than 56 years) (0.7 percent). Nonetheless, the data and conclusions from the gathered sample would give valuable insight into the pandemic's influence on travel patterns, especially among younger and more educated individuals in a developing nation.

Table 4-1. Summary of the Socio-Demographic Status of Respondents

Items	Description	Number of respondents	%
Gender	Male	224	75.9
	Female	71	24.1
Age	16-25	232	78.6
	26-35	51	17.3
	36-45	8	2.7
	46-55	2	0.7
	56-65	2	0.7
	above 65	0	0
Doses of vaccine taken	2 Doses	268	90.8
	1 Dose	19	6.4
	None, Registered for vaccine	5	1.7
	None, have not registered yet	3	1
Employment status	Employed	71	24.1
	Self employed	10	3.4
	Student	203	68.8
	Unemployment	11	3.7
Monthly household income	Less than 5000	12	4.1
	5000-10000	11	3.7
	11000-20000	23	7.8
	21000-30000	18	6.1
	31000-40000	19	6.4
	41000-50000	19	6.4
	More than 50000	127	43.1
	Prefer not to say	66	22.4
Household vehicle ownership			
Cycle	0	205	69.7
	1	77	26.1
	2	12	4.08
Motorcycle	0	245	83.05
	1	40	13.55
	2	6	2.03
	3+	4	1.35
Private car	0	194	66.21
	1	84	28.6
	2	15	5.11
Microbus	0	289	98.6
	1	4	1.4
Others	0	288	98.3
	1	5	1.7

4.3 Shift in Mode Choice by Socio-Demographic Characteristics

4.3.1 Gender

Male and female travelers comprise 76.1 percent and 23.9 percent, respectively, of the total number of respondents. The percentage of males and females who travel by bus is lower in the current circumstances than it was in the pre-covid era. On the other hand, rickshaw use has increased significantly in the present circumstances.

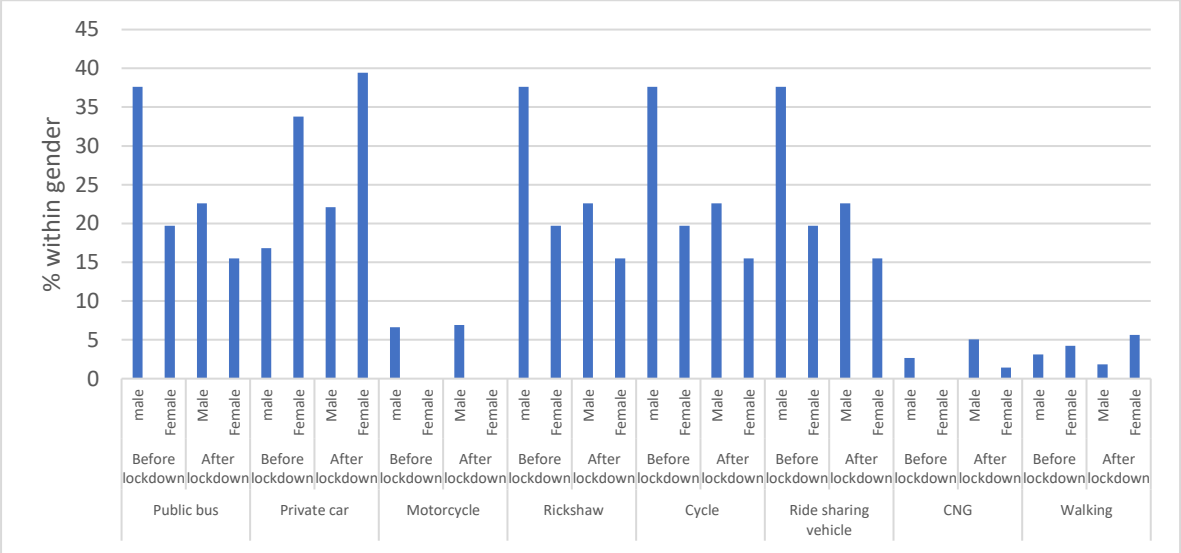


Figure 4-1. Modes Used by Different Genders in Pre and Post Lockdown Setting

4.3.2 Age

The majority of travelers (78.8 percent) are between the ages of 16 and 25 of the total number of respondents. In the pre-covid period, the majority of young people relied on bus services for mobility, but in present situation, they combine public transportation with other modes of transportation. On the other hand, senior citizens prefer other modes of transportation than the public bus.

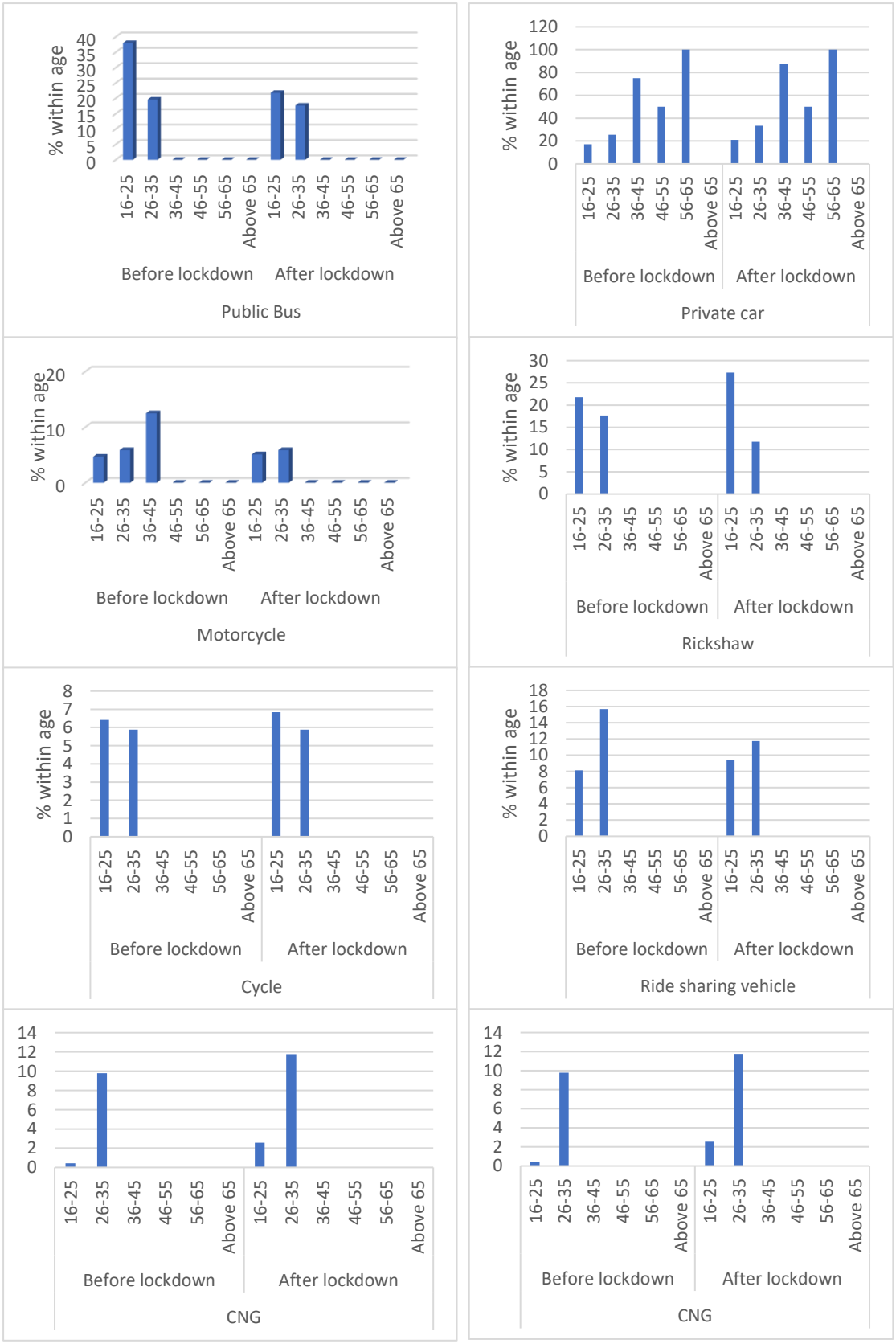
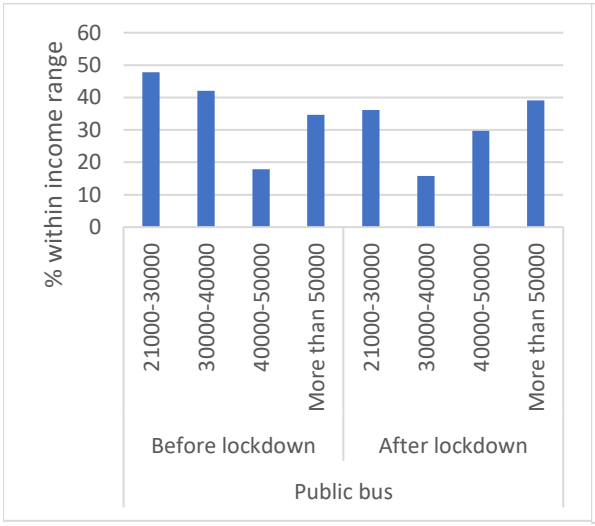
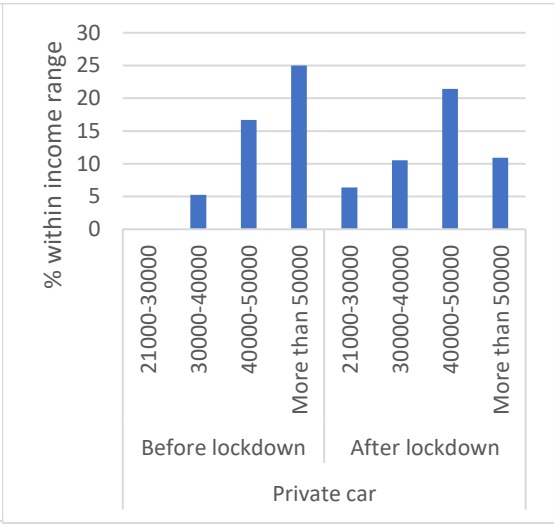


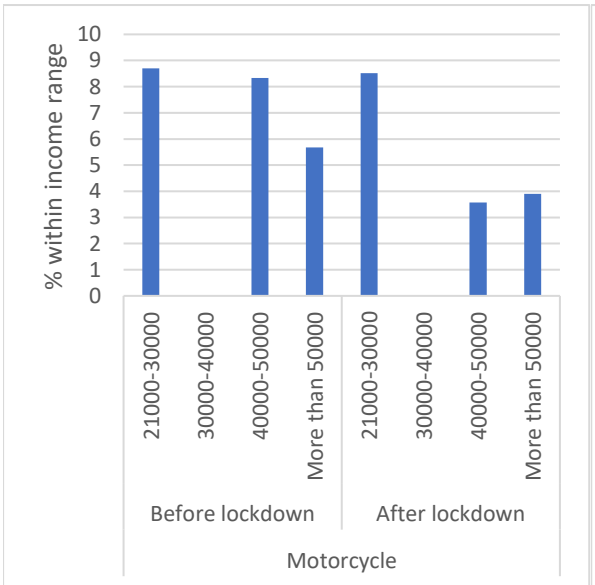
Figure 4-2. Modes Used by Different Ages in Pre and Post Lockdown Setting

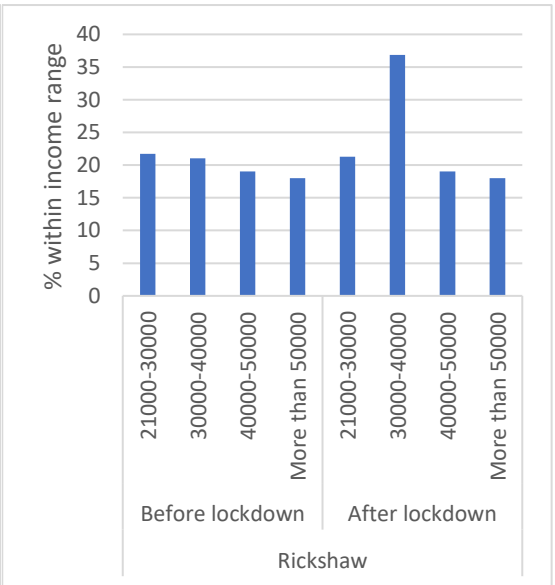
4.3.3 Income

The following table details the income distribution of commuters. It demonstrates that the majority of travelers' households (43.1 percent) earn more than 50,000 BDT monthly. Currently, individuals with a better household income choose private cars and other modes of transportation over public transit. Additionally, public bus usage is lower than it was before lockdown.









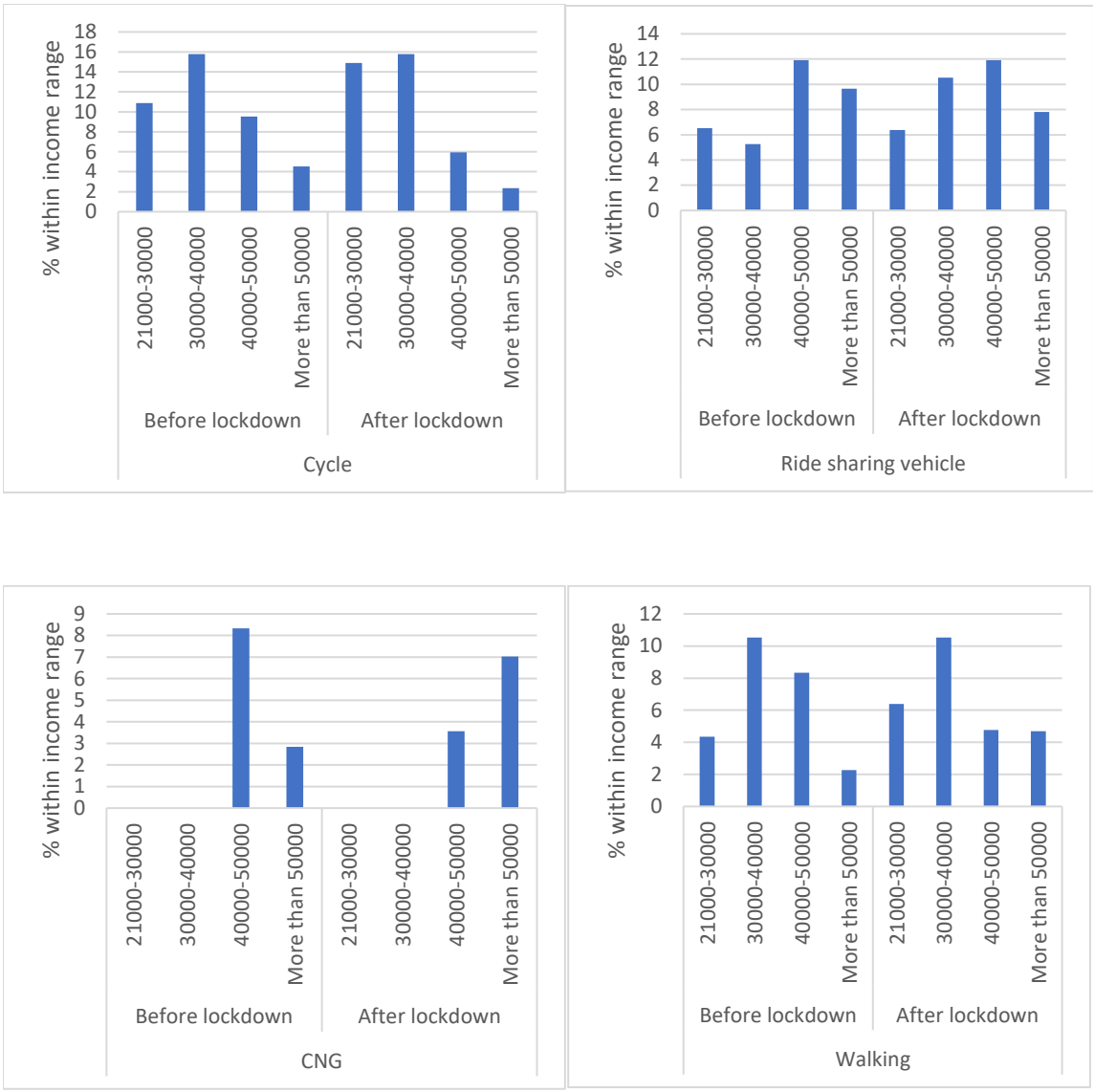
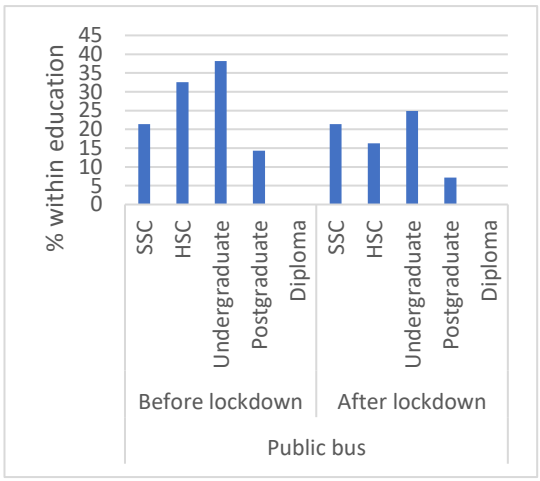
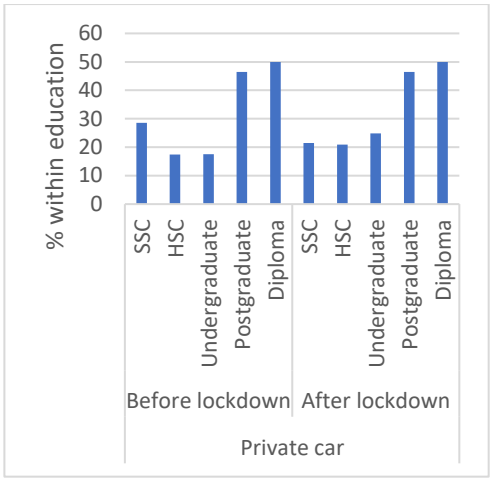


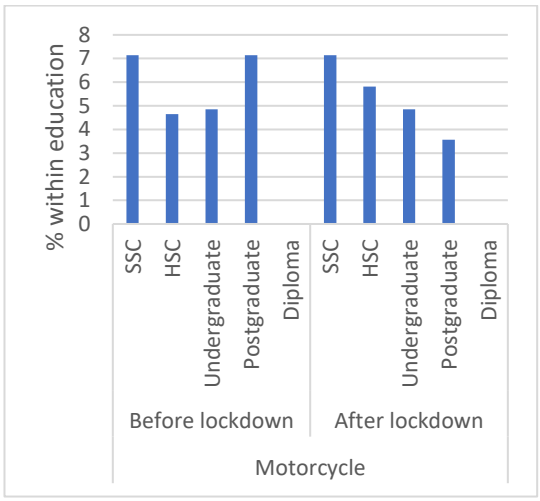
Figure 4-3. Mode of transportation used by travelers according to their household income before and after lockdown

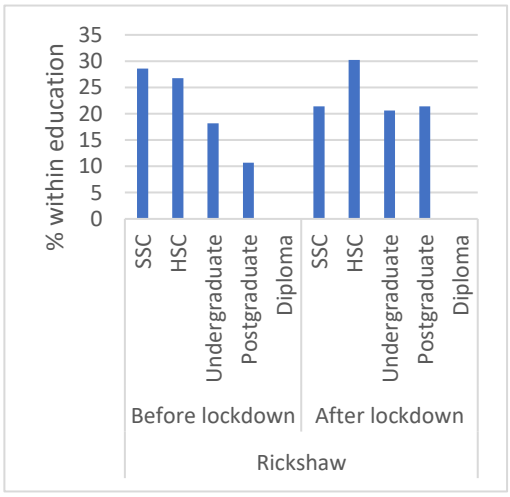
4.3.4 Education

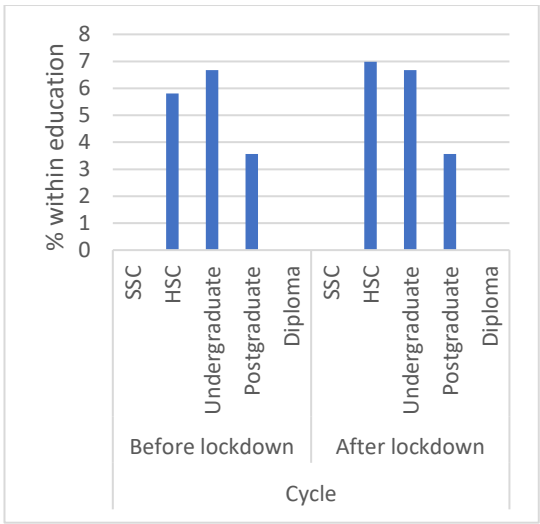
It is clear that the majority of respondents (48.1 percent) are undergraduates, and that their use of public transportation has fallen in recent years. Aside from that, the use of private cars and rickshaws has grown marginally.

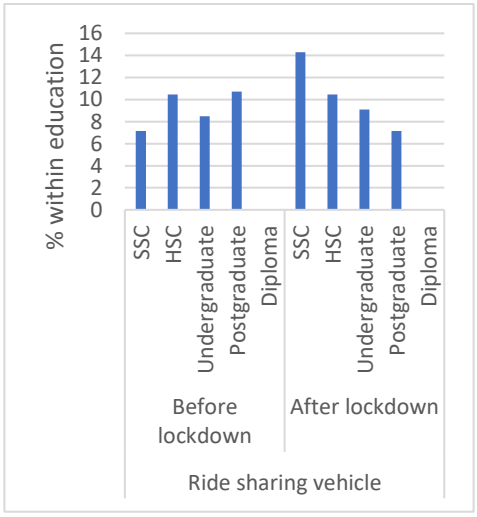

% within education
45
40
35
30
25
20
15
10
5
0
SSC
HSC
Undergraduate
Postgraduate
Diploma
SSC
HSC
Undergraduate
Postgraduate
Diploma
Before lockdown
After lockdown
Public bus


% within education
60
50
40
30
20
10
0
SSC
HSC
Undergraduate
Postgraduate
Diploma
SSC
HSC
Undergraduate
Postgraduate
Diploma
Before lockdown
After lockdown
Private car


% within education
8
7
6
5
4
3
2
1
0
SSC
HSC
Undergraduate
Postgraduate
Diploma
SSC
HSC
Undergraduate
Postgraduate
Diploma
Before lockdown
After lockdown
Motorcycle


% within education
35
30
25
20
15
10
5
0
SSC
HSC
Undergraduate
Postgraduate
Diploma
SSC
HSC
Undergraduate
Postgraduate
Diploma
Before lockdown
After lockdown
Rickshaw


% within education
8
7
6
5
4
3
2
1
0
SSC
HSC
Undergraduate
Postgraduate
Diploma
SSC
HSC
Undergraduate
Postgraduate
Diploma
Before lockdown
After lockdown
Cycle


% within education
16
14
12
10
8
6
4
2
0
SSC
HSC
Undergraduate
Postgraduate
Diploma
SSC
HSC
Undergraduate
Postgraduate
Diploma
Before lockdown
After lockdown
Ride sharing vehicle

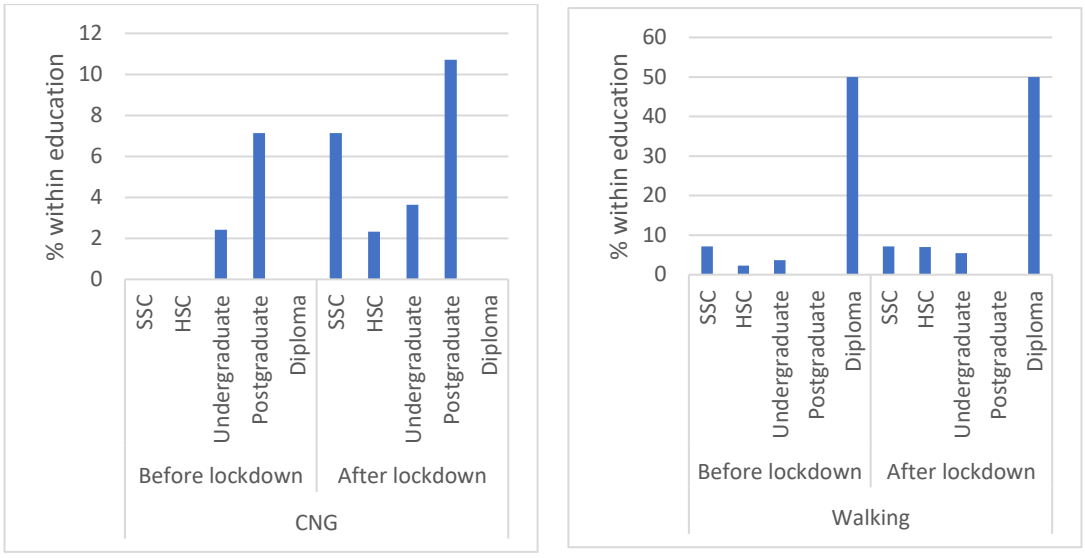
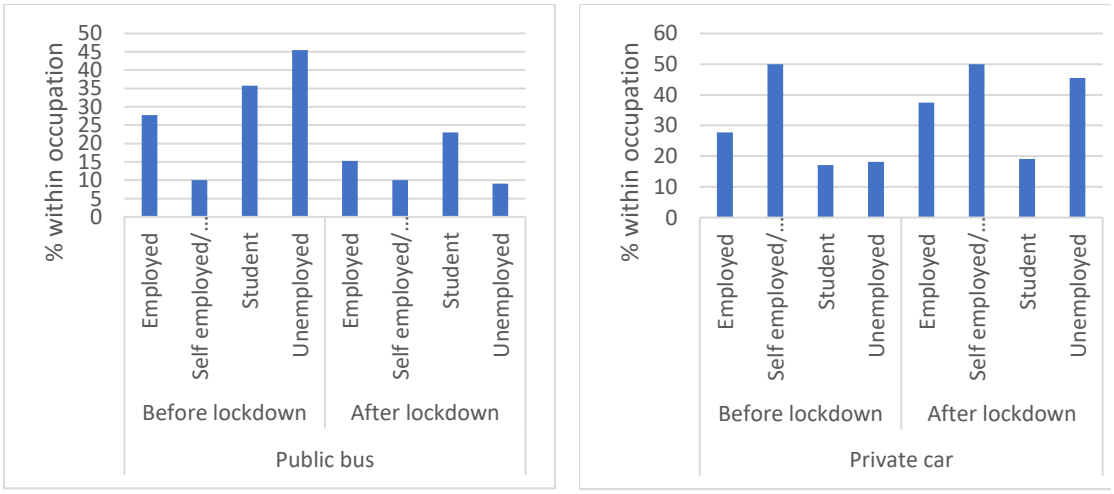
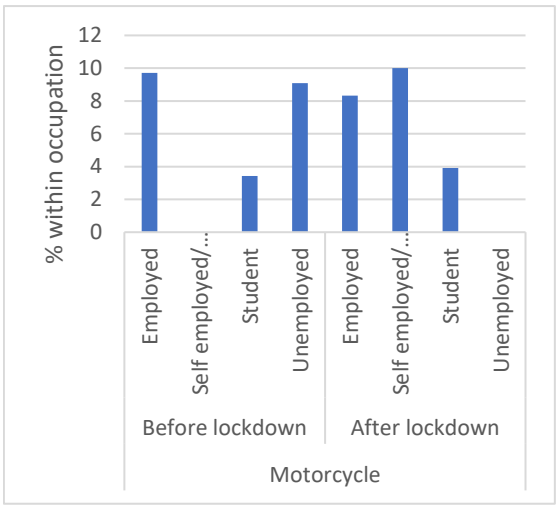


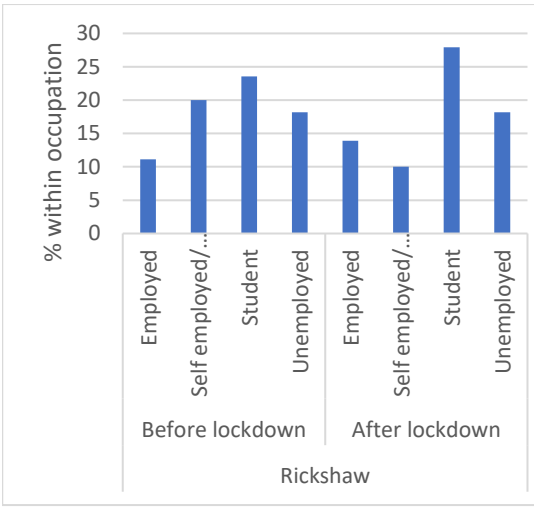
Figure 4-4. Mode of transportation used by travelers according to their education before and after lockdown

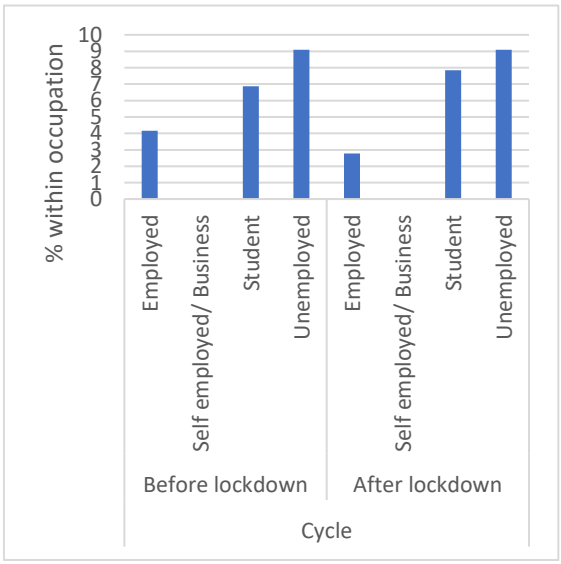
4.3.5 Occupation

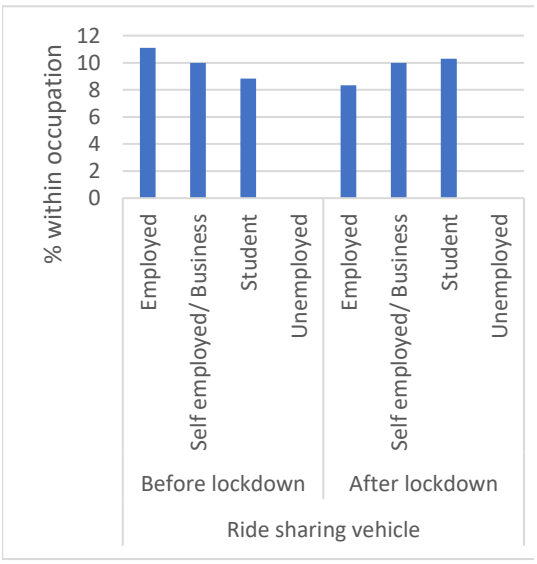
It has been found that the vast majority of those who answered the survey questions are students (68.7 percent). Initially, they favored public buses for pre-covid situations, but as time progressed, they preferred rickshaws, bicycles, and app-based ride-sharing vehicles. The use of private automobiles remains constant.




% within occupation
12
10
8
6
4
2
0
Employed
Self employed/...
Student
Unemployed
Employed
Self employed/...
Student
Unemployed
Before lockdown
After lockdown
Motorcycle


% within occupation
30
25
20
15
10
5
0
Employed
Self employed/...
Student
Unemployed
Employed
Self employed/...
Student
Unemployed
Before lockdown
After lockdown
Rickshaw


% within occupation
10
9
8
7
6
5
4
3
2
1
0
Employed
Self employed/ Business
Student
Unemployed
Employed
Self employed/ Business
Student
Unemployed
Before lockdown
After lockdown
Cycle


% within occupation
12
10
8
6
4
2
0
Employed
Self employed/ Business
Student
Unemployed
Employed
Self employed/ Business
Student
Unemployed
Before lockdown
After lockdown
Ride sharing vehicle

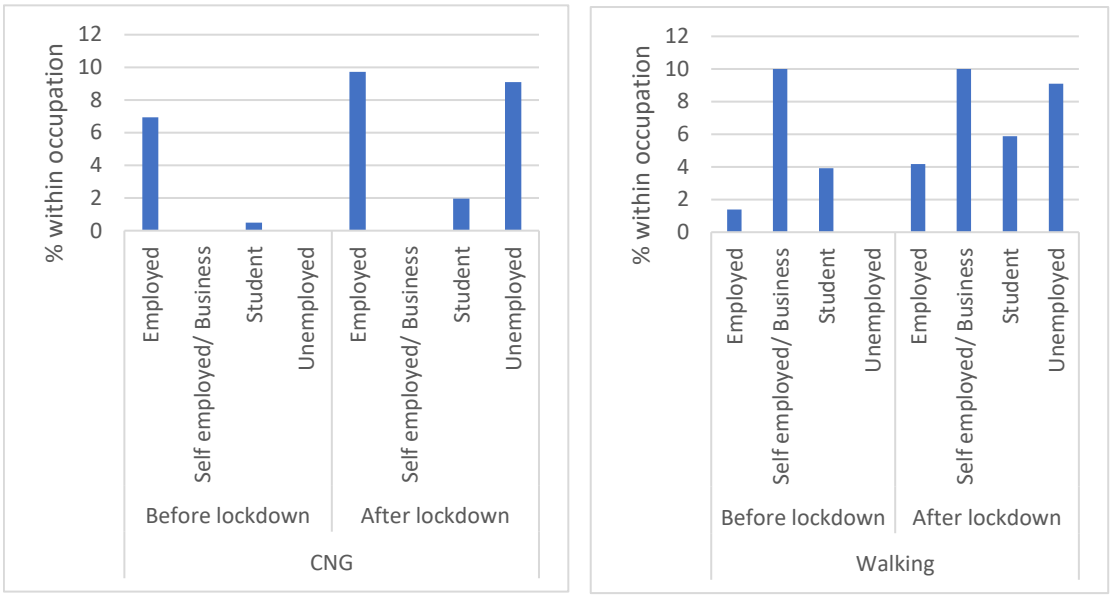
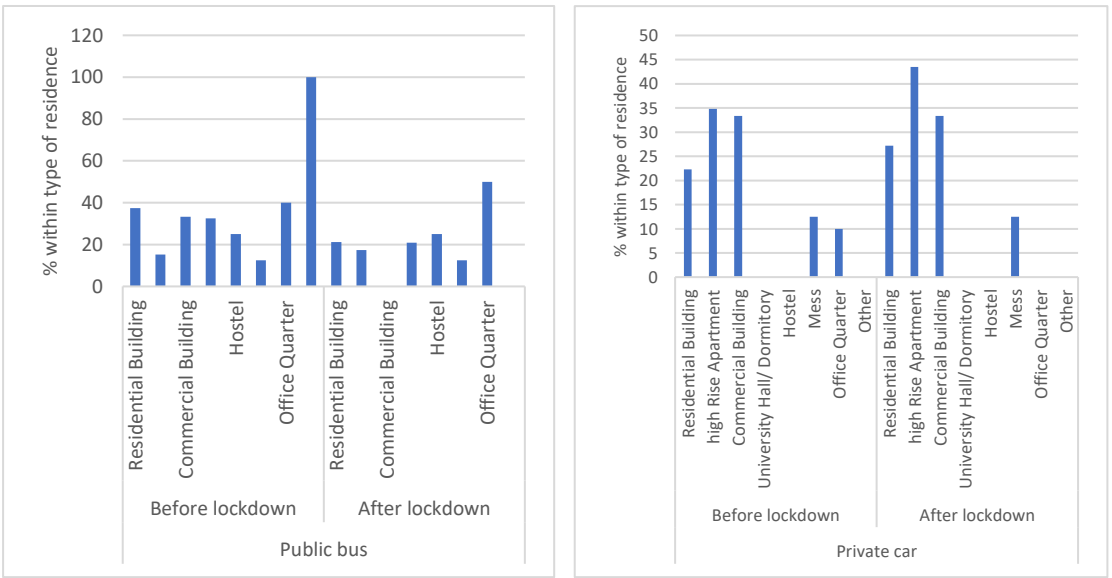


Figure 4-5. Mode of transportation used by travelers according to their occupation before and after lockdown

4.3.6 Type Of Residence

It has been observed that the great majority of people who responded to the survey questions are residents of residential buildings, according to the findings (62 percent). Those who used public buses before to the beginning of the Covid era have moved their means of transportation from public buses to rickshaws, CNG, and even walking.



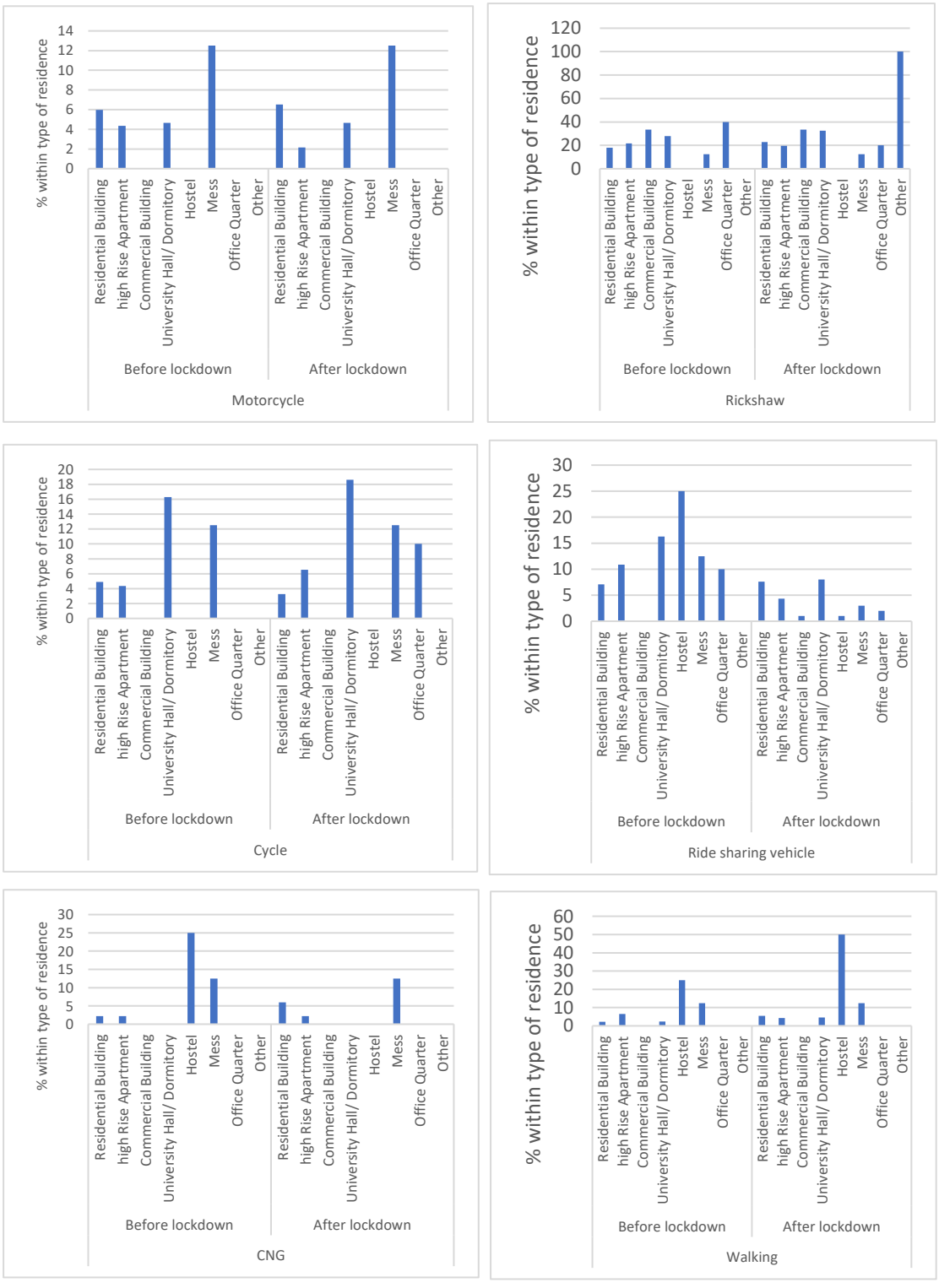


Figure 4-6. Mode of transportation used by travelers according to their type of residence before and after lockdown

4.3.7 Place Owning

64.3 percent of respondents mentioned that they rent/lease their residence. Their mode of transportation preference before to the Covid period and current circumstances are shown here.

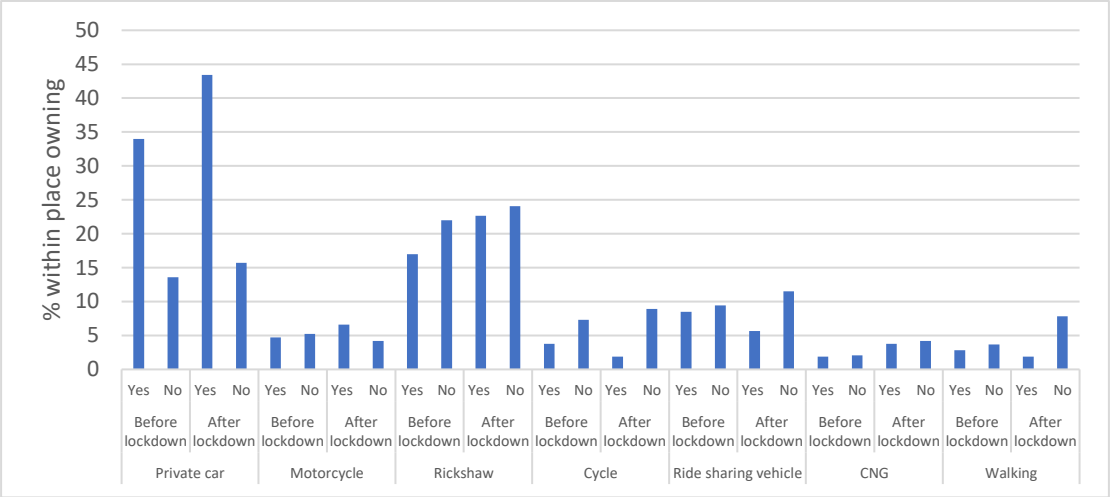


Figure 4-7. Mode of transportation used by travelers according to place owning before lockdown

4.4 Factors Affecting the Mode Choice Decision of the travelers

There are numerous factors that influence travelers' choice of mode before and after lockdown. The socioeconomic status of travelers, their travel behavioral patterns, and a few other significant factors all influence their mode choice. This chapter provides a detailed overview of the available factors influencing the mode choice behavior of Dhaka's travelers.

Table 4-2. Importance of different factors affecting the mode choice of the travelers before lockdown

Factors	Score	Rank
Safety	2.758503	1
Punctuality	2.707483	2
Trip distance	2.62585	3
Cost	2.608844	4
Comfort	2.486395	5
Accessibility	2.482993	6
Female seating availability	2.210884	7
Pollution level	2.210884	8
Crowding	2.14966	9
Condition	2.146259	10

Table 4-2. ***(continued)***

Factors	Score	Rank
Waiting time	2.108844	11
Noise level	2.085034	12
Disease transmission	1.534014	13

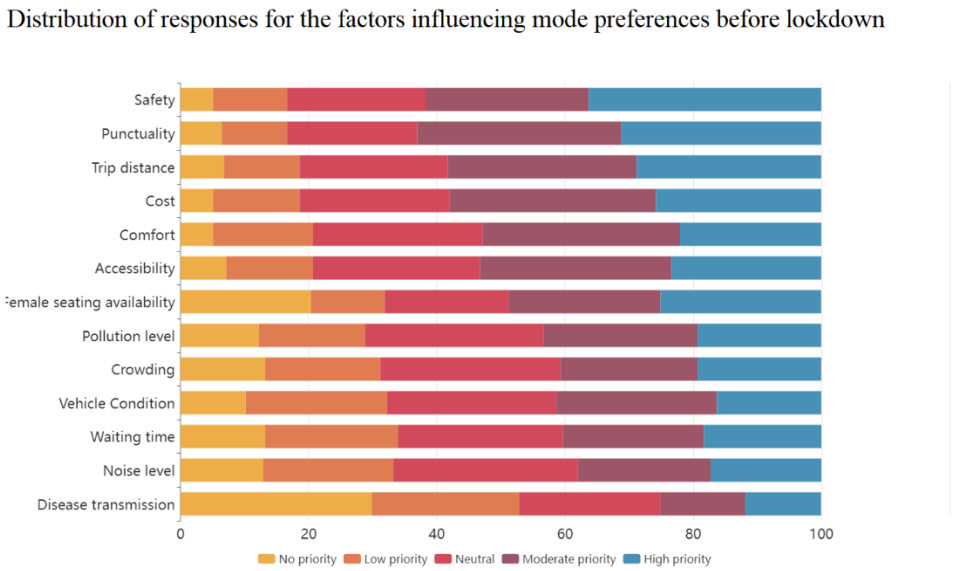


Figure 4-8. Distribution of responses for the factors influencing mode preferences before lockdown.

Table 4-3: Importance of different factors affecting the mode choice of the travelers after lockdown

Factors	Score	Rank
Safety	3.101694915	1
Disease transmission	2.979661017	2
Crowding	2.888135593	3
Punctuality	2.850847458	4
Trip distance	2.786440678	5
Comfort	2.650847458	6
Cost	2.637288136	7
Accessibility	2.637288136	8
Condition	2.627118644	9
Pollution level	2.525423729	10
Waiting time	2.420338983	11
Female Seating availability	2.328813559	12
Noise level	2.213559322	13

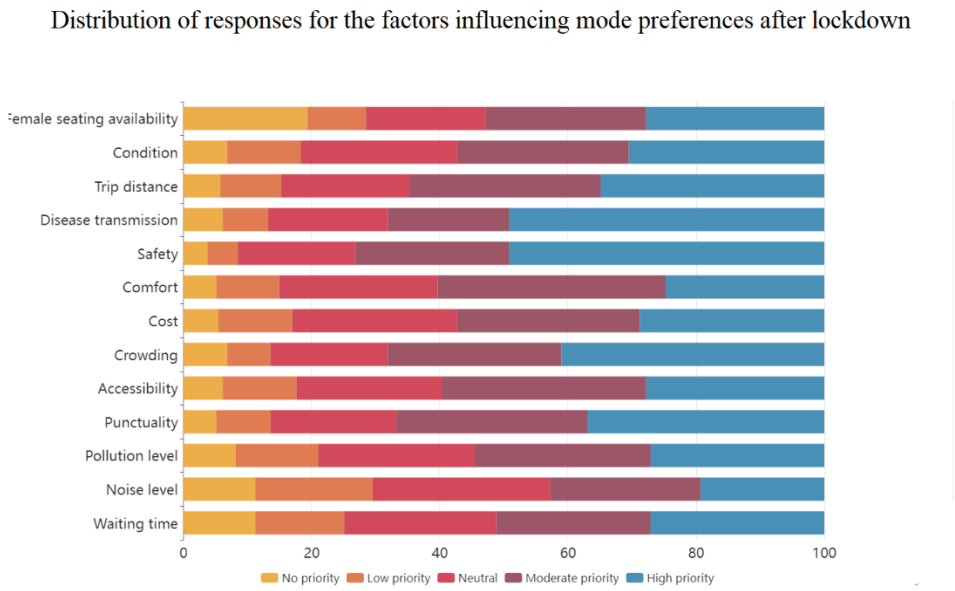


Figure 4-9. Distribution of responses for the factors influencing mode preferences after lockdown.

Under typical conditions, various considerations such as travel duration, cost, and comfort impact mode choice. However, other variables such as disease transmission, crowding may come into play during pandemic. Figure 4-8 and Figure 4-9 illustrate the distribution of responses to many parameters impacting mode preferences before to and throughout the pandemic. The majority of respondents prioritized pandemic-related things when selecting a mode of operation after lockdown. Table 4-2 and Table 4-3 shows the mean and order of the mode preference components. The mean of the respondents' priorities for each item indicated that respondents prioritized safety first, followed by disease transmission during the epidemic. Before lockdown, they prioritized safety, followed by punctuality. Priority was given to noise levels during the pandemic and disease transmission in public transportation vehicles before to the outbreak.

Wilcoxon Signed Rank tests were used to determine how individuals prioritized various issues before to and throughout the pandemic. As seen in Table 4-3, individuals placed a greater priority on disease transmission, safety, crowding, accessibility, punctuality, pollution, noise level, and waiting time during the pandemic. Surprisingly, personal social status continues to influence mode selection throughout the epidemic. It is worth noting that there was no discernible variation in the relative importance put on comfort and cost before to and during the epidemic. As a result, some characteristics

that influence mode selection in regular life may be less relevant after lockdown. On the other hand, whereas many pandemic-related mode choice criteria may be absent in regular daily life, they may become critical after lockdown.

4.5 Shift in Travel Purpose Before and After Lockdown

According to the findings of this study, the major traveling purpose is defined as the most significant reason for which individuals travel in their daily lives. Possibly, these are the trips over which individuals have little or no control at all. People may choose to decrease their trip for a variety of reasons, but they may be forced to travel for a variety of major ones. People travel for a variety of reasons, some of which are more important than others. For example, some people travel mainly for work, while others travel primarily for study. The major reason for traveling may change depending on the conditions, for example, during a pandemic outbreak.

Approximately 56 percent of those who responded said that their major reason for traveling was to study before the pandemic, but a smaller amount, 35 percent, stated that their primary reason for traveling was to study throughout the pandemic. It might be explained by the fact that many educational institutions have either entirely or partly moved to online education, which was predicted given the recent shift in educational trends. On the other hand, the percentage of respondents who stated that they were working as their primary purpose increased from 26 percent before the pandemic to 35 percent during the pandemic. This could be explained by the fact that students have started part-time jobs in order to make use of their spare time. Approximately 1.08 percent of respondents stated shopping as their primary traveling purpose throughout the pandemic, whereas only approximately 1.62 percent of respondents declared it as their primary traveling purpose prior to the pandemic, indicating that this is a consistent trend throughout the survey.

After the lockdown was removed, the McNemar tests indicated that the predominant motive for travel shifted significantly from study trips to business travels. There was also a major shift from travel for study to travel for shopping and travel for recreation. The reason for this is that online classes do not necessitate transportation, allowing students to go out for pursuing other interests.

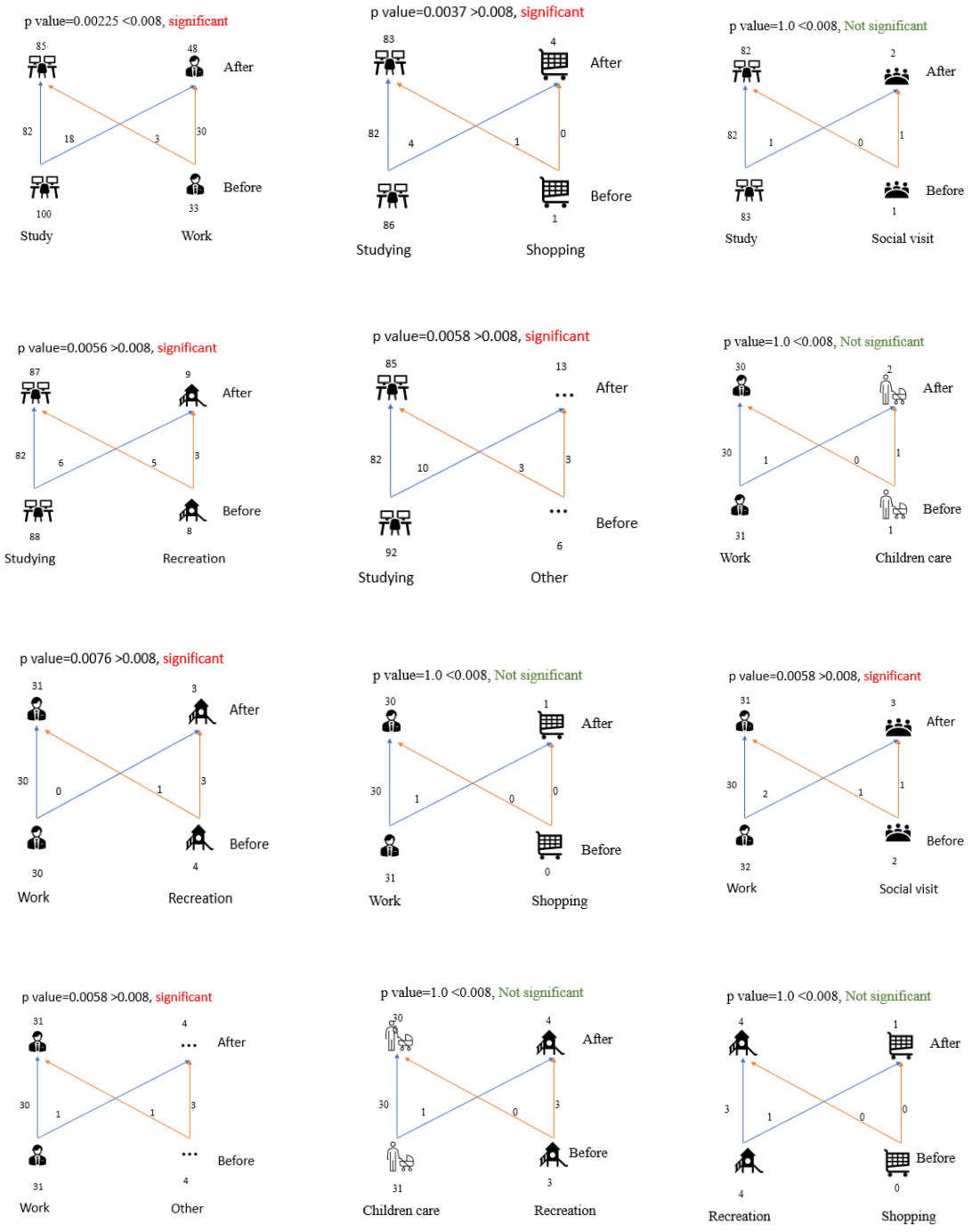


Figure 4-10. Before and after lockdown, shift in the primary purpose of travel (results of McNemar test)

Despite the fact that study trips decreased as a result of the pandemic, they still account for a significant share of all journeys (i.e., 35 percent). It might be ascribed to the fact that this poll was performed shortly after the lockdown was lifted, signaling that educational institutions were progressively resuming their activities following the event. Some students who lived in certain locations did not have access to the internet

at all, even when the school was closed. As a result, individuals were required to go to adjacent locations in order to get internet connection in order to participate in the online courses. Throughout the pandemic, it is possible that these excursions will account for a significant share of the research travels.

4.6 Non-commuting Trip Frequency

In contrast to commuting travels, such as work or study trips, non-commuting travels are ones that are not made on a daily basis. These include shopping, social visit, leisure activities, and other trips.

During the COVID 19 pandemic, travel frequency for non-commuting trips decreased. Approximately 9.82 percent of responders travel at least once every week throughout the pandemic. The Wilcoxon signed ranks test showed that there were statistically significant changes in the number of non-commuting trips made before to and during the pandemic (statistic=365, p value=0.0005).

Before and after lockdown, men made much more non-commuting trips than females. One factor might be that financial responsibility for a home is traditionally attributed to males. Additionally, women are sometimes prevented from venturing outdoors under the guise of guarding themselves from sexual violence (Narjis Rizvi, 2014).

Employed individuals made much more non-commuting trips than students throughout the pandemic, although this difference was not significant prior to the outbreak. One probable explanation for this is because trips are likely to be correlated with both employment status and social duties.

4.7 Preferred Modes

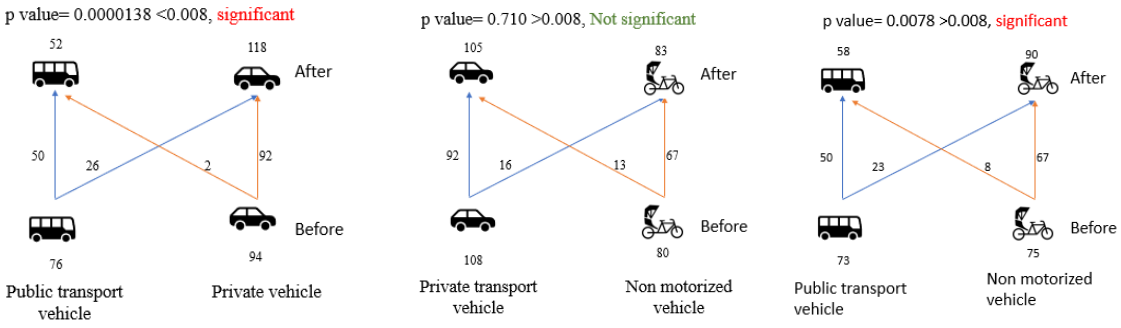


Figure 4-11. Mode shift due to COVID-19 (results of McNemar test).

The McNemar test found that a large modal shift occurred from public transport vehicle to private vehicle, which might be linked to individuals feeling unsafe in public transport vehicle owing to their close proximity to other people. Existing data indicates that individuals are more inclined to prioritize their health than their economic well-being. However, the proportion of private car usage increased and a panel survey done in Istanbul, Turkey found that car owners preferred to travel by car during the pandemic due to fear of infection (Shakibaei, 2021).

Significant modal shift from public transportation vehicles to non-motorized vehicles is seen. After the onset of the COVID 19 pandemic period, tiemakers began to prioritize issues that they had previously ignored, which led them to favor non-motorized vehicles over public transportation vehicles.

Modeling Mode Choice and Analysis

5.1 Introduction

The second objective of the study was to develop mode choice models to identify the changes in mode choice factors between the before lockdown and after lockdown situations. To that end, three different logit models have been developed, corresponding to the pre-lockdown mode choice model, post-lockdown mode choice model and model denoting the change in mode choice factors. The models consider eleven (11) different socio-demographic, seven (7) trip-related variables and three (3) reduced variables of Levels of Service (LOS) attitude obtained from Exploratory Factor Analysis (EFA) and they were used for estimation of the parameters of the models. For the modes, Public Transport (PT), Private Vehicle (PV) and Non-Motorized Vehicle (NMV) were available choices. Firstly, the statistical significance of each parameter of the model and the model as a whole were determined. Secondly, the reasonableness and comparison of the magnitude of the parameters of the model were examined. Thirdly, the cross-validation and accuracy of the model was checked.

5.2 Available Modes

Commuters' mode choice usually involves a combination of multiple modes. However, for our analysis we considered only the single home-based trips most frequented by the respondents and assumed that the mode mentioned was used for the entirety or majority of the trip length. The modes were grouped into three distinct categories after analysis of correlation among the modes. Only the modes that the responses contained were considered, despite being available in the study area. Thus, a total of three mode types were considered for this study and the Public Transport (PT) was considered as reference mode for comparison **(Table 5-1)**. PT denoted multi-passenger vehicles, which operated on fixed routes and could not be catered specifically to any passenger's origin-destination pairs. Juxtaposing, Private Vehicle (PV) were concerned with vehicles that were dependent on the passenger's specific origin-

destination and could adapt to Level of Service (LOS) condition of the planned route. The last category, Non-Motorized Vehicle (NMV) were short distance modes that depended on passengers' specific trip plans and required some efforts from them.

Table 5-1. Modes Used in the Models

Mode Group	Basis of Categorization	Descriptors
Public Transport (PT)	Multi-Person Fixed Route Vehicles	Public Bus
		Human Hauler
Private Vehicle (PV)	Motorized Demand Responsive Transports	Private Car
		Motorcycle
		CNG
Non-Motorized Vehicle	Low Speed Non-Motorized Demand Responsive Transports	Rickshaw
		Cycle
		Walking

5.3 Dimensionality Reduction for High Correlation

The variables were checked for high correlation among themselves first, as high correlations may lead to malfunctioning of the logit models and the best practice is to reduce the variables to latent variables that can explain the effects of the highly correlated variables. To that end, correlation matrices of the variables for pre-Lockdown and post-Lockdown were constructed and are shown in **Figure 5-1 and Figure 5-2**.

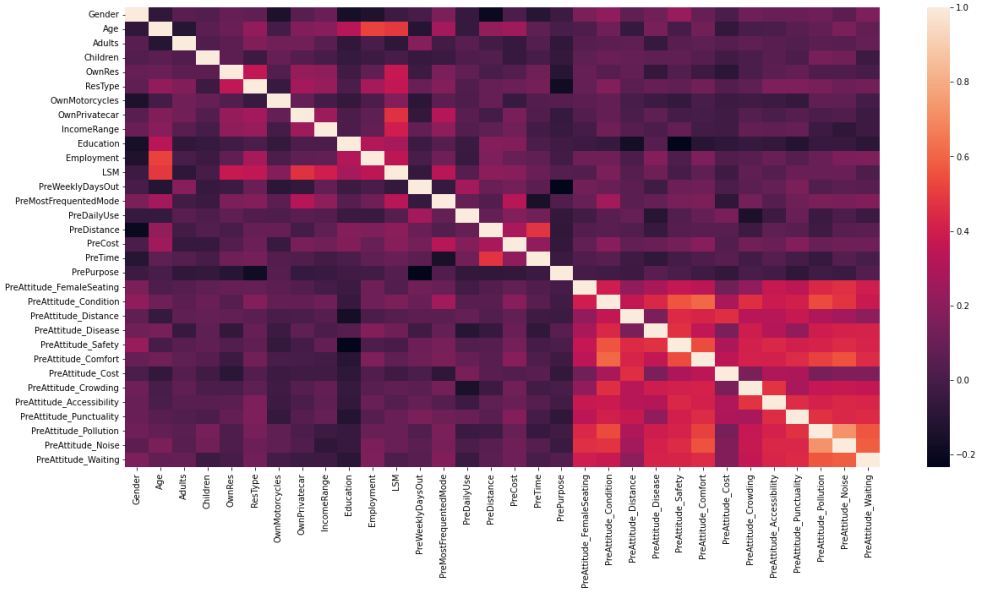


Figure 5-1. Correlation Matrix of pre-Lockdown variables

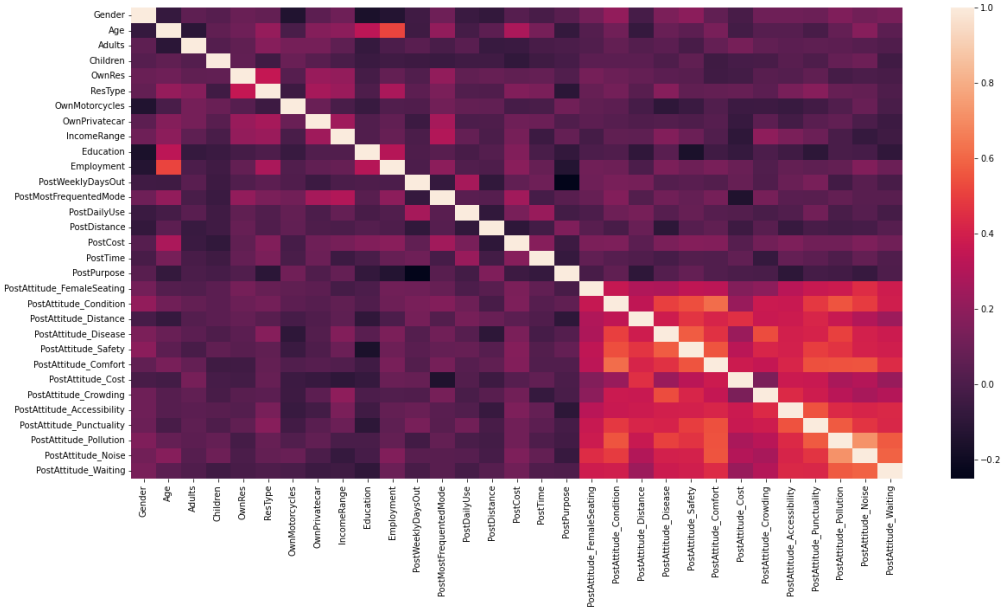


Figure 5-2. Correlation Matrix of post-Lockdown variables

The matrices show that the variables representing the Importance Imparted on various vehicle, trip and safety conditions were highly correlated to each other and thus needed to be reduced. Thus, the variables were needed to be reduced. There are various options for dimensionality reduction, however, similar research suggested attitude variables are best reduced using Exploratory Factor Analysis (EFA). Thus, to check effectiveness of EFA, Bartlett's Test of Sphericity and Kaiser-Meyer-Olkin (KMO) Test were needed to be conducted. The outputs received by the test were denoted marvelous, as both values for pre and post lockdown were nearly 0.90 and were greater than the cutoff point of 0.7. The p-values obtained for the pre and post-lockdown attitude data from Bartlett's Test of Sphericity were very low and close to zero. A value below 0.05 is considered to be significant, entailing the point that the data has worthwhile correlations. Thus, the attitude variables were significant for reduction using EFA and the outputs of the tests are summarized in **Table 4-2**.

Table 5-2. Outputs of KMO and Bartlett's Test of Sphericity for EFA

Test Name	Cutoff Points	Data Considered	Output
Kaiser-Meyer-Olkin (KMO Test)	> 0.7	Pre-Lockdown	0.8982
		Post-Lockdown	0.9076
Bartlett’s Test of Sphericity	< 0.05	Pre-Lockdown	0.000
		Post-Lockdown	0.000

5.3.1 Exploratory Factor Analysis (EFA)

while conducting EFA, eigenvalue can be interpreted as the proportion of the information in a factor. The cut-off of 1 means the factor contains information = 1 item. Thus, it is not worthwhile keeping factor with information < 1 item. The plot is called 'Scree Plot', which is based on eye-ball judgement of an eigenvalue vs number of factors plot. Look for the number of eigenvalue points/factors before eigenvalue is reduced to zero. **Figure 5-3** outlines the scree plot and shows that three (3) factors are required to explain most of the variances of the variables.

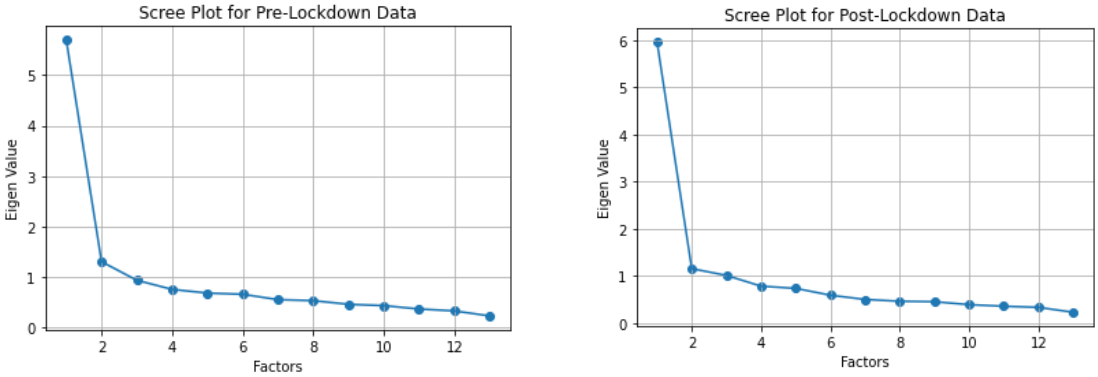


Figure 5-3. Scree Plot of the two Data

Following that, the variables were reduced to three latent factors that most represented their variances. Seeing the coherence in the grouped variables some intuitive name that qualitatively represents the latent factors was given. **Table 5-3** and **Table 5-4** outlines the name of the variables, the reduced latent factors associated with such, and the proportion of variances explained by the latent factors for pre-lockdown and post-lockdown data.

Table 5-3. Summary of the Latent Factors for Pre-Lockdown Variables

Variable Name	Communalities	Latent Factor Name	Proportion of Variance Explained	Cumulative Variance Explained
PreAttitude_FemaleSeating	0.311674	External Attributes Related	0.214324	0.214324
PreAttitude_Accessibility	0.394405			
PreAttitude_Punctuality	0.446736			
PreAttitude_Pollution	0.677617			
PreAttitude_Noise	0.704882			
PreAttitude_Waiting	0.501689			

Table 5-3 ***(continued)***

PreAttitude_Condition	0.546315	Safety And Distancing Related	0.147315	0.361638
PreAttitude_Disease	0.464784			
PreAttitude_Safety	0.561151			
PreAttitude_Crowding	0.379601			
PreAttitude_Distance	0.527175	Trip Related	0.133550	0.495188
PreAttitude_Comfort	0.547089			
PreAttitude_Cost	0.374333			

Table 5-4. Summary of the Latent Factors for Post-Lockdown Variables

Variable Name	Communalities	Latent Factor Name	Proportion of Variance Explained	Cumulative Variance Explained
PostAttitude_FemaleSeating	0.26397	External Attributes Related	0.230227	0.230227
PostAttitude_Accessibility	0.410975			
PostAttitude_Punctuality	0.519467			
PostAttitude_Pollution	0.68822			
PostAttitude_Noise	0.74879			
PostAttitude_Waiting	0.469596			
PostAttitude_Condition	0.504362	Safety And Distancing Related	0.177748	0.407975
PostAttitude_Disease	0.581845			
PostAttitude_Safety	0.555001			
PostAttitude_Crowding	0.448192			
PostAttitude_Distance	0.466048	Trip Related	0.113227	0.521202
PostAttitude_Comfort	0.546052			
PostAttitude_Cost	0.573103			

The naming of the variables were just based on previous comprehension and have no arbitrary significance. The communalities of the variables were also significant. These transformed variables are used in the following models.

5.4 Rationale for Selection of Variables/Hypothesis

Initially, all potential variables were included in the model. However, some variables having little or no influence on mode choice have been excluded for a better model fit. Variables with low statistical significance were consequently discarded. Also, highly correlated variables like importance imparted on Level of Service (LOS) attributes were also reduced using Exploratory Factor Analysis (EFA). The socio-

demographic status and incurring variables were assumed constant in both pre-lockdown and post-lockdown setting, while the LOS and Importance Imparted variables were different in pre and post setting.

Table 5-5. List of Variables Used in the Models

Types of Variables	Variable Name	Variable Notation
-	Alternative Specific Constant	ASC_PT, ASC_PV, ASC_NMV
Socio-Demographic Variables	Gender Dummy	Gender
	Age	Age
	Number of Adults in HH	Adults
	Number of Children in HH	Children
	HH Owns Residence	OwnRes
	Type of Residence Dummy	ResType
	Number of Motorcycles Owned by HH	OwnMotorcycle
	Number of Private Cars Owned by HH	OwnPrivatecar
	Monthly Income Range of Household	IncomeRange
	Level of Education Dummy	Education
	Employment Status Dummy	Employment
Travel Behavior and Trip Specific Variables	Number of Days Mode Used in a Week (Pre-Lockdown, Post-Lockdown)	PreWeeklyDaysOut, PostWeeklyDaysOut
	Number of Times Mode Used in a Day (Pre-Lockdown, Post-Lockdown)	PreDailyUse, PostDailyUse
	Mode Used in Most Frequented Trip (Pre-Lockdown, Post-Lockdown)	PreMostFrequentedMode, PostMostFrequentedMode
	Distance Travelled by Mode in Most Frequented Trip (Pre-Lockdown, Post-Lockdown)	PreDistance, PostDistance
	Cost incurred on Most Frequented Trip (Pre-Lockdown, Post-Lockdown)	PreCost, PostCost
	Travel Time for a Single Trip (Pre-Lockdown, Post-Lockdown)	PreTime, PostTime
	Purpose of Most Frequented Trip (Pre-Lockdown, Post-Lockdown)	PrePurpose, PostPurpose

Table 5-5 ***(continued)***

Types of Variables	Variable Name	Variable Notation
Attitude Towards LOS Attributes	External Attributes of Mode (Pre-Lockdown, Post-Lockdown)	PreVariable1, PostVariable1
	Safety & Distancing in Mode (Pre-Lockdown, Post-Lockdown)	PreVariable2, PostVariable2
	Trip Related Attributes	PreVariable3, PostVariable3
Comparison Related	Time Period Dummy	TimePeriod

5.4.1 Statistical Significance

After examining the sign of the estimated coefficients, the importance of individual coefficients was assessed for each model. In practice, a significance level of between 0.05 and 0.01 is typical, but different values are often employed. In creating a decision rule, a significance threshold of 0.10 has been used due to the study's small sample size (295). Then there are around 10 out of 100 odds that we would reject the hypothesis when it should be accepted; hence, we are approximately 90% positive that we have chosen the correct choice.

5.4.2 Goodness of Fit Statistics

With the estimate of many specifications, it is useful to compare metrics of goodness of fit. A Multinomial Logit Model specification with a greater maximum value of the likelihood function is deemed superior. Comparing the McFadden's pseudo R-squared value of the models is more convenient. It is similar to the R-squared values of normal regression in that a larger number is generally preferable. This value calculates the ratio between the log-likelihood of the supplied model and the log-likelihood of a "intercept-only" model. The reported value is then determined by subtracting from 1 the ratio determined in step two. A small ratio (and thus a final result near to 1) implies that the stated model is superior to a model based just on the intercept.

5.4.3 Interpretation of Parameter Estimates

The various interpretations of the interaction model to understand qualitative change in the variables of the pre and post lockdown models is undertaken. The significance of the changes and the sign based qualitative change is tabulated for each mode in each analysis. Public Transport (PT) is the reference mode; thus, all comparisons are based on conversion from PT to the mode under consideration. Also, the base period is pre-lockdown; thus, changes of effects of variables on mode choice model in a post-lockdown setting is outlined. However, the changes of the impacts need to be cross-validated. However, as the models are very similar in consideration of variables, model structure and log likelihood ratios, they can be directly compared.

5.5 Mode Choice Model Before Lockdowns

The available mode classes were more than three, thus, Multinomial Logit Model was used. It is assumed that IIA property holds true for this model, thus MNL model was incorporated. The process of model specification is described in the following sections.

5.5.1 Model Specification

To maintain homogeneity between the before lockdown and after lockdown (denoted Pre and Post) models and make it easier to draw inferences, the variables that were statistically significant at the stated Level of Significance were considered for both models, which are outlined in **Table 5-5**. Due to the nature of Multinomial Logit Model, PT was taken as reference category and two models were developed for PV and NMV with direct comparison to PT. The variables with "Pre" prefix were considered along with the socio-demographic and attitude related variables. Public Transport (PT) was considered as reference outcome and thus, the probability of other modes and odds ratio was calculated against it. The Goodness of Fit (GoF) measures of the MNL model, the estimation coefficients, the statistically significant level, Odds Ratio and Confidence Interval of Odds Ratios of the variables obtained from the analysis are shown in **Table 5-6, Table 5-7** and **Table 5-8**. The model exhibits a likelihood value that is better than an intercept-only model. The test statistics of likelihood ratio rejects the null hypothesis implying their different level of impacts on mode choice in a pre-lockdown situation. The pseudo R-Squared value of the model is excellent and accounts for 46.82% of the variances. The model accurately identifies 74.23% of the mode choices of the dataset.

The model estimation is statistically significant, and multi-collinearity is not present in the model; therefore, the standard errors of the regression coefficient β have a value of no more than 4. On the other hand, regression coefficients of the independent variables are measured by calculating the change in the logit for a one-unit change in the predictor variable while the other predictor variables are kept constant. To analyze the model, we have discussed and focused on independent variables related to dependent variables, which have statistical significance less than 0.1 being based on the model results. Consequently, model interpretation will only focus on these variables.

Table 5-6. Goodness of Fit Measures of Pre-Lockdown Model

Model GoF Measures	
Estimated Parameters	21
Number of Observations	295
Final Log likelihood	-171.57
Null log likelihood	-322.61
Significance	0.0000
Chi-Square	302.08
McFadden's R-Squared	0.4682

Table 5-7. Estimation of Coefficients, the Statistically Significant Level, Odds Ratio and Confidence Interval of Odds Ratios of the Variables of the Multinomial Logit Model in Pre-Lockdown Setting for Private Vehicles

Variables	**Coeff.**	**Sig.**	**Odds Ratio**	**Confidence Interval of Odds Ratio**	
Private Vehicles (PV)				**Lower Bound**	**Upper Bound**
Intercept	0.353	0.701	1.423338	0.234447	8.641132
Gender	0.6041	0.188	1.82963	0.744834	4.494349
Age	1.5302	0.006	4.619266	1.542006	13.83757
Adults	0.0183	0.914	1.018445	0.731569	1.417817
Children	-0.2042	0.289	0.81528	0.558896	1.189277
OwnRes	0.1189	0.785	1.126287	0.48024	2.641436
ResType	0.2716	0.138	1.312086	0.916636	1.878139
OwnMotorcycles	0.7475	0.002	2.111723	1.305556	3.415691
OwnPrivatecar	-0.3591	0.307	0.698284	0.350798	1.389973
IncomeRange	-0.1108	0.539	0.895142	0.62861	1.274685
Education	-0.171	0.328	0.842863	0.598588	1.186823
Employment	-0.5307	0.099	0.588214	0.308859	1.120236
_PreWeeklyDaysOut	-0.1315	0.214	0.876771	0.712457	1.078982

Table 5-7. ***(continued)***

Variables	Coeff.	Sig.	Odds Ratio	Confidence Interval of Odds Ratio	
Private Vehicles (PV)				Lower Bound	Upper Bound
PreDailyUse	0.2931	0.019	1.340552	1.048857	1.713369
PreDistance	-0.3692	0.009	0.691255	0.523933	0.912012
PreCost	0.2909	0.035	1.337676	1.021404	1.751878
PreTime	-0.7001	0.000	0.496533	0.337579	0.730333
PrePurpose	0.8494	0.023	2.338321	1.121442	4.875636
PreVariable1	-0.1407	0.52	0.868758	0.565804	1.333927
PreVariable2	0.9299	0.001	2.534313	1.47968	4.340629
PreVariable3	0.073	0.749	1.075718	0.687269	1.683722

Table 5-8. Estimation of Coefficients, the Statistically Significant Level, Odds Ratio and Confidence Interval of Odds Ratios of the Variables of the Multinomial Logit Model in Pre-Lockdown Setting for Non-Motorized Vehicles

Variables	Coeff.	Sig.	Odds Ratio	Confidence Interval of Odds Ratio	
Non-Motorized Vehicle (NMV)				Lower Bound	Upper Bound
Intercept	-1.1025	0.249	0.33205	0.050929	2.16492
Gender	0.9025	0.047	2.465843	1.012828	6.003373
Age	1.4692	0.005	4.345808	1.555268	12.14327
Adults	-0.0878	0.603	0.915971	0.657964	1.275151
Children	-0.3791	0.061	0.684447	0.460663	1.016942
OwnRes	0.7547	0.069	2.126893	0.944013	4.791962
ResType	0.0305	0.864	1.03095	0.728144	1.459681
OwnMotorcycles	0.3409	0.178	1.406202	0.856633	2.308345
OwnPrivatecar	0.9496	0	2.584669	1.524341	4.382559
IncomeRange	0.1814	0.308	1.198933	0.845912	1.699281
Education	-0.1693	0.352	0.844242	0.590924	1.206154
Employment	-0.1443	0.628	0.86559	0.482744	1.552057
_PreWeeklyDaysOut	-0.179	0.099	0.836094	0.675845	1.034339
PreDailyUse	0.2516	0.04	1.286083	1.01096	1.636079
PreDistance	0.078	0.561	1.081167	0.830839	1.406918
PreCost	0.608	0	1.836836	1.382562	2.440371
PreTime	-0.7677	0	0.464066	0.32136	0.670144
PrePurpose	0.3667	0.415	1.44293	0.597346	3.485495
PreVariable1	0.3905	0.086	1.477776	0.94613	2.308163
PreVariable2	0.451	0.091	1.569861	0.930676	2.648037
PreVariable3	-0.1962	0.401	0.821886	0.519905	1.29927

5.5.2 Interpretation of Parameter Estimates

For Private Vehicles (PV) model:

1) The results indicate that the one-unit increase in the independent variable (Age) is associated with a 4.61 increase in the relative log odds of choosing a private vehicle against choosing public transport. This result shows that older respondents incline to travel by private vehicles with personal O-D pair more than by using other transport modes.

2) Results also show that the variable of the ownership of motorcycles in household which indicates that the one-unit increase in the independent variable is associated with 2.111723 times increase in the coefficient of choosing a private vehicle. This confirms that the presence of privatized vehicles in a household has a strong statistical influence to reduce public transport use.

3) The variable employment has a negative relationship (-0.5307) with the outcome of car, denoting that students are more likely to prefer public transport over private vehicles. Unemployed population are most likely to prefer public transport as it may save their transportation costs.

4) With 2.338321 times more chances at influencing a mode choice decision from being the use of PT to PV, the purpose of the trip was significant for travelers as they preferred their Routine Purposes (Education-Work-Children Work) to use PT due to high frequency of those and prefer to use PV for less frequent trips. Similar results can be seen for the variable PreDailyUse representing the daily use of a mode.

5) For Distance and Travel Time of the trip, a negative change can be observed, meaning that for longer trips both spatially and temporally, users tend to prefer PT. This is counterintuitive to our priori expectations, as PV provides more comfort for longer trips. However, an explanation of such behavior can be explained with concerns for costs, as longer distances and time incurs higher cost on PV than PT. This is also exhibited with the positive change in PreCost variable, denoting PV incurring higher cost on users.

6) Safety and distancing related variable (PreVariable2) created 2.53 times more change in choosing PV over PT, meaning that travelers deemed PV to be less crowded, safer and low-risk.

For Non-Motorized Vehicle (NMV) model:

1) Gender, Age, Number of Private Cars Owned, Number of Daily Use of Mode, Cost of Travel, Importance Imparted on External Attributes of Mode and Safety and Distancing related variables had positive implications on choosing NMV over PT. That means, if these variables increase, so does the chances at choosing NMV over PT. That can be explained as, females tend to choose NMV over PT due to safety concerns, Older people tend to use NMV than PT, Higher frequency of short distance trips tend to prioritize NMV and compared to NMV travelers tend to view PT as unsafe and unpredictable sort of mode, leading to picking NMV over PT even for long distance trips if they can bear the costs. However, compared to our priori assumptions, sign of coefficient for number of private cars owned differed significantly, as increase in private car is sure to shift consumers from NMV to PV. For the first model, the effect of change in number of private cars in household was insignificant, thus, effect of this variable can be widely discarded over the two models.

2) Number of Children in Household, Number of Days Out in a Week, Travel Time incurred negative coefficient with significant change on outcome. This can be explained by the fact that the increase of number of children in household may lead to incapability of using a single NMV for a single trip and thus, they may use PT instead of NMV. Furthermore, if the travelers travel multiple days a week, due to cost consideration from previous point, they may prefer PT for similar distance trips. Also, if PT is preferred if travel time is higher for NMV.

5.6 Mode Choice Model After Lockdowns

Similar to the Pre-Lockdowns models, this model incorporated Multinomial Logit Model due to availability of multiple mode choices set as outcomes. Just like the previous setting, two different models for PV and NMV were created, and the outcomes

were compared. The process of model specification is described in the following sections.

5.6.1 Model Specification

To maintain homogeneity between the before lockdown and after lockdown (denoted Pre and Post) models and make it easier to draw inferences, the variables that were statistically significant at the stated Level of Significance were considered for both models, which are outlined in Table 4-2. The variables with "Post" prefix were considered along with the socio-demographic and attitude related variables. Public Transport (PT) was considered as reference outcome and thus, the probability of other modes and odds ratio was calculated against it. Although, all the available variables that were considered in the study are not listed, the final model performed better than previous ones with all variables considered. The Goodness of Fit (GoF) measures of the MNL model, the estimation coefficients, the statistically significant level, Odds Ratio and Confidence Interval of Odds Ratios of the variables obtained from the analysis are shown in **Table 5-9, Table 5-10** and **Table 5-11**. The model exhibits a likelihood value that is better than an intercept-only model. The test statistics of likelihood ratio rejects the null hypothesis implying their different level of impacts on mode choice in a post-lockdown situation. The values are also very close to the pre-lockdown models which means the models are very comparable. The pseudo R-Squared value of the model is excellent and accounts for 47.44% of the variances. The model accurately identifies 76.27% of the mode choices of the dataset. The model estimation is statistically significant, and multi-collinearity is not present in the model; therefore, the standard errors of the regression coefficient β have a value of no more than 4. On the other hand, regression coefficients of the independent variables are measured by calculating the change in the logit for a one-unit change in the predictor variable while the other predictor variables are kept constant. To analyze the model, we have discussed and focused on independent variables related to dependent variables, which have statistical significance less than 0.1 being based on the model results. Consequently, model interpretation will only focus on these variables.

Table 5-9. Goodness of Fit Measures of Post-Lockdown Model

Model GoF Measures	
Estimated Parameters	21
Number of Observations	295
Final Log likelihood	-163.11
Null log likelihood	-310.33
Significance	0.0000
Chi-Square	293.78
McFadden's R-Squared	0.4744

Table 5-10. Estimation of Coefficients, the Statistically Significant Level, Odds Ratio and Confidence Interval of Odds Ratios of the Variables of the Multinomial Logit Model in Post-Lockdown Setting for Private Vehicles

Variables	**Coeff.**	**Sig.**	**Odds Ratio**	**Confidence Interval of Odds Ratio**	
Private Vehicles (PV)				**Lower Bound**	**Upper Bound**
Intercept	1.7761	0.081	5.907057	0.802244	43.49465
Gender	0.1844	0.707	1.202443	0.45939	3.147363
Age	0.1207	0.831	1.128338	0.372027	3.422183
Adults	-0.0204	0.91	0.979769	0.688766	1.393721
Children	-0.2142	0.275	0.807217	0.549339	1.186151
OwnRes	0.1893	0.67	1.208348	0.50589	2.886208
ResType	-0.1132	0.536	0.892997	0.623763	1.278441
OwnMotorcycles	0.5317	0.054	1.701896	0.991146	2.922326
OwnPrivatecar	-0.6458	0.076	0.52424	0.256766	1.07034
IncomeRange	0.4393	0.032	1.55157	1.039606	2.315656
Education	-0.2384	0.194	0.787915	0.550019	1.128705
Employment	0.2822	0.451	1.326067	0.63613	2.764297
_PostWeeklyDaysOut	-0.2014	0.042	0.817602	0.67342	0.992653
PostDailyUse	0.0625	0.633	1.064459	0.823442	1.376021
PostDistance	0.0242	0.845	1.024448	0.803852	1.305583
PostCost	0.1308	0.299	1.139718	0.890265	1.459069
PostTime	-0.6266	0	0.534419	0.396319	0.720642
PostPurpose	0.4543	0.196	1.575017	0.791055	3.135912
PostVariable1	0.0466	0.83	1.047693	0.684977	1.602478
PostVariable2	0.4006	0.085	1.492689	0.94569	2.356079
PostVariable3	-0.1351	0.597	0.873636	0.529257	1.442098

Table 5-11. Estimation of Coefficients, the Statistically Significant Level, Odds Ratio and Confidence Interval of Odds Ratios of the Variables of the Multinomial Logit Model in Post-Lockdown Setting for Non-Motorized Vehicles

Variables	Coeff.	Sig.	Odds Ratio	Confidence Interval of Odds Ratio	
Non-Motorized Vehicle (NMV)				Lower Bound	Upper Bound
Intercept	-0.0516	0.961	0.949728	0.121131	7.446362
Gender	0.6462	0.179	1.908283	0.744284	4.892683
Age	0.3781	0.481	1.45945	0.510202	4.17481
Adults	-0.1249	0.496	0.882556	0.615824	1.264819
Children	-0.2754	0.179	0.759242	0.508032	1.134671
OwnRes	0.8344	0.05	2.303425	1.000813	5.301456
ResType	-0.2153	0.233	0.806314	0.566214	1.148227
OwnMotorcycles	0.6107	0.028	1.841713	1.068721	3.173802
OwnPrivatecar	0.5327	0.058	1.703591	0.981422	2.95716
IncomeRange	0.5844	0.003	1.793868	1.21657	2.645112
Education	-0.2123	0.253	0.808694	0.562117	1.163432
Employment	0.6793	0.06	1.972419	0.97236	4.001024
PostWeeklyDaysOut	-0.1413	0.166	0.868236	0.710829	1.0605
PostDailyUse	0.0414	0.745	1.042309	0.811952	1.338021
PostDistance	0.0653	0.586	1.067472	0.843854	1.350349
PostCost	0.3346	0.006	1.397398	1.099667	1.775738
PostTime	-0.2038	0.157	0.815637	0.614976	1.081773
PostPurpose	0.1544	0.684	1.166986	0.555166	2.453063
PostVariable1	0.0529	0.815	1.054277	0.677183	1.641359
PostVariable2	0.473	0.044	1.604857	1.01249	2.543796
PostVariable3	-0.5194	0.045	0.594894	0.357653	0.989502

5.6.2 Interpretation of Parameter Estimates

For Private Vehicles (PV) model:

1) Income Range of HH, Number of Motorcycles owned by HH and Importance on Safety and Distancing related variables were significant in changing mode choice from PT to PV in Post-Lockdown settings. It can be inferred that compared to Pre-Lockdown settings income range and financial status is a more important factor in mode choice. People with higher financial status are tending towards safer alternatives in new normal as they can bear the costs, but people with lower status are still tending towards public transport without any options. Number of Motorcycles owned by HH is a common factor in both pre and post

lockdown setting. However, people are imparting more importance on safety and distancing attributes of modes, as they are prioritizing uncrowded and distanced environments, which is provided by PV.

2) Number of Cars owned by HH, Number of Days out in a week and Travel time in post lockdown situation exhibits a negative relationship, implying that an increase in these factors persuaded travelers to shift from PV to PT. Similar to the Pre-Lockdown model, the effect of the number of cars owned by HH is counterintuitive and can be dismissed. Due to cost considerations people are still considering PT over PV, if they have to make the same trip more times in a week or if the trip is expected to take longer than usual, which were also observed in the pre-lockdown model.

3) Age, Employment Status, Purpose of the trip, Distance travelled were no longer significant compared to pre-lockdown model. Thus, it can be argued that people are no longer providing any importance to these variables while choosing PV over PT. However, it can also be explained by the fact that the effect of external variables out of consideration of this study influenced the model leading to less significance imparted on these variables. This can be confirmed through an interaction analysis of the variables to the Pre and Post Lockdown periods which will be done in the following section.

For Non-Motorized Vehicle (NMV) model:

1) Ownership of Residence, Income Range of HH, Employment Status, Number of Motorcycles Owned by Household, Cost of Travel and Importance Imparted on Safety & Distancing related factors had positive influence towards the outcome, providing insights that people with higher financial status tended to avoid PT in new normal situation due to fear of disease transmission and their ability to bear cost. Self Employed or Employed personnel were more likely to use NMV in the new normal, and, the number of motorcycles owned by household were a major factor in using NMV, as, due to less use of PT they may utilize NMV in some trips.

2) Change in one unit of Importance Imparted on Trip Related Attributes, Number of Days out weekly and Number of Private Cars owned by household, shifted the mode choice from NMV to PT. This provides insight that, travelers, despite the fear of disease transmission, still provided more priority on distance, time and cost of trip while choosing PT than NMV. If they had to provide less priority on these while making a trip-related decision, they tended to go for NMV. Also, if the trips are less frequent, they preferred NMV. Also, ownership of cars tended to shift travelers towards PT, which again is counterintuitive.

1) Compared to pre-lockdown model, gender, age, number of daily uses of mode, external attributes of mode, number of children in HH and travel time were not significant in post-lockdown situation while choosing NMV. It may be possible that these were not significant any longer, or it may be that the model attempted to impart less significance on these to attain a better fit.

5.7 Comparative Analysis of Interaction Between Pre and Post Lockdown Models

As it was observed in the interpretations of the coefficients and odds ratio of the models, there were some losses of significance for some variables in the two periods. It would be valid to infer that these variables were no longer significant in a post-lockdown setting. However, as Logit Models tend to fit the data for best likelihood estimates, it can also be inferred that the model prioritized these variables less for a better fit. Thus, to gain understanding of the changes incurred in mode choice behavior from a pre-lockdown situation to a post-lockdown situation and to get better understanding of how much changes were actually incurred qualitatively, it was required to create an interaction model that will show the changes of the variables with respect to the time periods. The following sections expand on this analysis method and the observed outcomes.

5.7.1 Model Specification

Interactions between the pre-defined variables and TimePeriod Compared to the two models stated above that tended to work with either pre or post variables, this model takes considers all variables regardless of time. Thus, the Pre and Post suffixes are

removed. However, a new variable called TimePeriod, which is the time period dummy indicating whether the observation is set in Pre-Lockdown or Post-Lockdown setting was introduced. A value of zero indicated that the observation was for pre-Lockdown and one denoted post-Lockdown time period. Similar to the previous models, the socio-demographic variables, the mode and trip specific variables and the importance imparted on LOS variables were considered. However, due to the merging of the data, total observations were doubled to five hundred and ninety (590). Furthermore, new interaction variables were introduced that denoted the variables. These variables were denoted as "Variable:TimePeriod" which means the interaction of the variable with the time period. A simplified version considering only Age and TimePeriod variables of the modified equation for the Interaction based multinomial logit model can be represented as follows:

$$logit(y) = \beta_0 + \beta_1 \cdot Age + \beta_2 \cdot TimePeriod + \beta_3 \cdot Age \cdot TimePeriod$$

Where TimePeriod is the indicator variable for the post-Lockdown time period. Time period is 1 when the observation is for post-lockdown situation. Pre-Lockdown time period acts as reference. The likelihood ratio test tests the following hypotheses:

$$\mathrm{H}_0 : \beta_3 = 0$$
$$\mathrm{H}_1 : \beta_3 \neq 0$$

So, it tests whether the differences between the age slope of pre-lockdown and post-lockdown models differ significantly. If the likelihood ratio test is significant, it provides evidence that at the two models have different slopes

Public Transport (PT) was considered as reference outcome and thus, the probability of other modes and odds ratio was calculated against it as before. The Goodness of Fit (GoF) measures of the MNL model, the estimation coefficients and the statistically significance level of the variables and the interaction variables obtained from the analysis are shown in **Table 5-12, Table 5-13** and **Table 5-14**. The likelihood test rejects the null hypothesis implying that the influence of the variables does indeed vary significantly between pre and post lockdown siuations. The values are also very close to the pre-lockdown models which means the models are very comparable. To analyze the change in slope, we again used statistical significance of 0.1 as the cutoff,

a value below which denotes that the change of impacts of the variables in pre and post lockdown situation were significant.

Table 5-12. Goodness of Fit Measures of the Interaction Model

Model GoF Measures	
Estimated Parameters	42
Number of Observations	590
Final Log likelihood	-191.11
Null log likelihood	-411.33
Significance	0.0000
Chi-Square	440.44

Table 5-13. Estimation of Coefficients, the Statistically Significance Level of the interaction model for Private Vehicles (PV)

Variables	**Coeff.**	**Sig.**
Private Vehicles (PV)		
Gender:TimePeriod	0.4171	0.045
Age:TimePeriod	-1.4099	0.077
Adults:TimePeriod	-0.0384	0.876
Children:TimePeriod	-0.0101	0.971
OwnRes:TimePeriod	0.0705	0.91
ResType:TimePeriod	-0.3853	0.137
OwnMotorcycles:TimePeriod	0.216	0.059
OwnPrivatecar:TimePeriod	-0.2847	0.574
IncomeRange:TimePeriod	0.5505	0.043
Education:TimePeriod	-0.0664	0.793
Employment:TimePeriod	0.8114	0.093
WeeklyDaysOut:TimePeriod	-0.0694	0.632
DailyUse:TimePeriod	-0.2305	0.203
Distance:TimePeriod	-0.1938	0.036
Cost:TimePeriod	-0.4603	0.039
Time:TimePeriod	0.0737	0.767
Purpose:TimePeriod	-0.3948	0.442
Variable1:TimePeriod	0.2882	0.041
Variable2:TimePeriod	0.5303	0.032
Variable3:TimePeriod	-0.2072	0.046

Table 5-14. Estimation of Coefficients, the Statistically Significance Level of the interaction model for Non-Motorized Vehicle

Variables	Coeff.	Sig.
Non-Motorized Vehicle (NMV)		
Gender:TimePeriod	-0.2534	0.001
Age:TimePeriod	-1.0915	0.146
Adults:TimePeriod	-0.0365	0.884
Children:TimePeriod	0.1036	0.019
OwnRes:TimePeriod	0.0796	0.893
ResType:TimePeriod	-0.2458	0.331
OwnMotorcycles:TimePeriod	0.2699	0.472
OwnPrivatecar:TimePeriod	-0.4159	0.286
IncomeRange:TimePeriod	0.4033	0.03
Education:TimePeriod	-0.0416	0.873
Employment:TimePeriod	0.8219	0.079
WeeklyDaysOut:TimePeriod	0.0381	0.798
DailyUse:TimePeriod	-0.21	0.035
Distance:TimePeriod	-0.0125	0.044
Cost:TimePeriod	-0.2735	0.049
Time:TimePeriod	0.5640	0.017
Purpose:TimePeriod	-0.2119	0.719
Variable1:TimePeriod	-0.3371	0.093
Variable2:TimePeriod	0.2219	0.031
Variable3:TimePeriod	-0.3226	0.056

5.7.2 Interpretation of Parameter Estimates

The various interpretations of the interaction model to understand qualitative change in the variables of the pre and post lockdown models is explained here. The significance of the changes and the sign based qualitative change is tabulated for each mode. As before, PT is the reference mode, thus all comparisons are based on conversion from PT to the mode under consideration. Also, the base period is pre-lockdown; thus, changes of effects of variables on mode choice model in a post-lockdown setting is outlined.

5.7.2.1 *For Private Vehicles (PV) model*

The changes are tabulated in **Table 5-15.** Some inference and contextual understandings are explained following the table.

Table 5-15. Qualitative Change in Slope in Variables Between Pre and Post Lockdown Situations for Private Vehicle (PV)

Variables	Significant Change?	Slope Change
Private Vehicle (PV)		
Gender	Yes	+0.4171
Age	Yes	-1.4099
Adults	No	-
Children	No	-
OwnRes	No	-
ResType	No	-
OwnMotorcycles	Yes	+0.216
OwnPrivatecar	No	-
IncomeRange	Yes	+0.4392
Education	No	-
Employment	Yes	+0.8114
_WeeklyDaysOut	No	-
DailyUse	No	-
Distance	Yes	-0.1938
Cost	Yes	-0.4603
Time	No	-
Purpose	No	-
Variable1	Yes	+0.2882
Variable2	Yes	+0.5303
Variable3	Yes	-0.2072

Inferences:

1) Gender, Number of Motorcycles Owned by HH, Income Range of HH and Employment Status of Travelers have significant positive change in their slopes between pre and post lockdown models. This signifies that, while choosing PV over PT, the impact of these characteristics of the traveler has increased. This is coherent with our descriptive statistics, as women tended to change their modes from PT to PV in post lockdowns and the other variables can be similarly explained.

2) Age, Distance, Cost of the trips and the reduced variable denoting the importance imparted on trip characteristics (Variable 3) had a negative significant change. This meant that people imparted less importance on the trip

characteristics, the distance and the cost of travelling, while choosing a mode in post lockdown. This is coherent with each other, as travelers used PV over PT despite cost and distance considerations or even time considerations. As a result, PV are getting used despite any trip considerations and the importance of such factors have reduced in Post Lockdown situation.

3) Importance imparted on Vehicle Safety & External factors and Safety & Distancing related variables have increased significantly. It can be interpreted as such that travelers are prioritizing the vehicle conditions, personal safety, noise, pollution, crowding and fear of disease transmission more, which leads them to choose PV more than PT. Being such, it can be said that travelers are more conscious about themselves, their health, safety and the natural environment as well and prefer transportations that have more safety provisions in place.

4) The changes are coherent with the changes identified by direct comparison of Pre and post lockdown models in the cases of Income Range of HH, Number of Motorcycles Owned by HH, Age, Distance, Importance Imparted on Safety & Distancing Variables. Effects of Gender, Employment Status, Cost were new, meaning the models had tried to polarize these variables for better fit, but in direct comparison these had changes in post-Lockdown situation. Similar interpretation can be imparted on Number of Cars owned by HH, Number of Days out in a week and Travel time, which were considered significant in post-lockdown model, but they were considered to not be so in interaction model. In such case, the interaction model can be considered valid more than direct comparison of the two models' coefficients.

5.7.2.2 *For the Non-Motorized Vehicle (NMV) model*

The changes are tabulated in **Table 5-16.** Some inference and contextual understandings are explained following the table.

Table 5-16. Qualitative Change in Slope in Variables Between Pre and Post Lockdown Situations for Non-Motorized Vehicle (NMV)

Variables	Significant Change?	Slope Change
Non-Motorized Vehicle (NMV)		
Gender	Yes	-0.2534
Age	No	-
Adults	No	-
Children	Yes	+0.1036
OwnRes	No	-
ResType	No	-
OwnMotorcycles	No	-
OwnPrivatecar	No	-
IncomeRange	Yes	+0.4033
Education	No	-
Employment	No	-
_WeeklyDaysOut	No	-
DailyUse	Yes	-0.21
Distance	Yes	-0.0125
Cost	Yes	+0.049
Time	Yes	+0.5640
Purpose	No	-
Variable1	Yes	-0.3371
Variable2	Yes	+0.2219
Variable3	Yes	-0.3226

Inferences:

1) Income Range of HH, Cost of Trip, Time of Trip, Safety and Distancing related variables had more impact on choosing NMV over PT or vice versa in new normal situation. These are coherent with the interpretation of the previous model.

2) Impacts of Gender, Number of Daily Uses of the Mode, Distance of the trip, Variables relating to the importance imparted on Vehicle condition & safety and Trip Attributes were less prominent in the new normal. This means, they had less influence in changing mode choice decision of PV to PT or vice versa in new normal than pre-lockdown times.

3) Changes in impacts of number of motorcycles owned by HH, number of cars owned by HH, Number of Days out in a week were considered to not be significant. Influence of Employment Status was deemed to not be significant either, which means that the model was trying to best fit data in this case.

5.8 Summary

In this chapter, a pre-lockdown model was created as a base to compare and for validation of data compared to priori assumption, then a post-lockdown model was estimated to identify impact of changes in the variables leading to mode choice and finally to cross-validate the change in impacts, an interaction model was constructed. The model found significant changes in some variables that matched with priori assumption and the changes were validated by interaction model as well. The results and findings are summarized in a following chapter.

Results and Discussion

6.1 Introduction

This chapter presents the findings of the research. The discussion on the results can be presented in this chapter also. The discussion of results can also be presented in a separate chapter. If the findings are distinct enough, the results can be presented in more than one chapter also. The results may be organized as per the specific aims mentioned in Chapter 1.

6.2 Changes in the Travel & Mode Choice Behavior

The analysis, done through descriptive statistics and non-parametric tests, exhibited various changes in mode choice and mode choice factors between pre and post lockdown settings. The pre-lockdown model acted as the base of comparison and the changes of the post-lockdown model were checked against it. There were significant changes in post-lockdown setting that has led the study for further analysis on the shifts incurred in mode choice.

6.2.1 Modal Shift

The **Figure 6-1** was constructed to showcase the vehicle composition and their shift in pre-lockdown and post-lockdown setting. The inter-modal shifts were further characterized by McNemar test that showed that the changes were significant. The result of the McNemar Test is summarized in **Table 6-1**. A margin of error of 10% was used, as the sample size was small and required a looser level of significance, however it meant that our analysis was 90% confident of identifying the changes and thus, could be used as a basis of comparison. Several discussions and interpretations can be obtained from the results and are discussed following the figure and table.

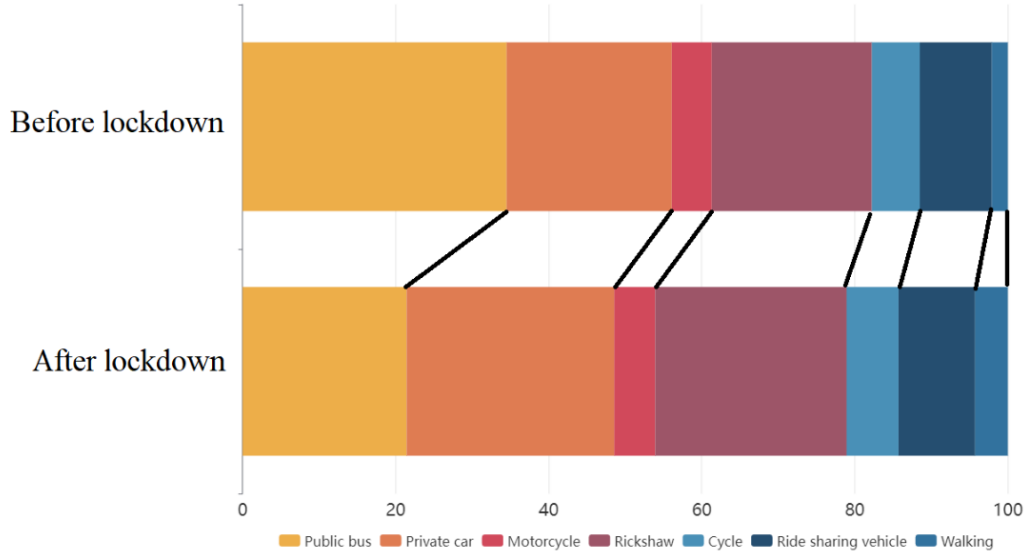


Figure 6-1. Vehicle Composition in Before and After Lockdown Setting

Table 6-1. Summary of the Intermodal Shift Analysis by McNemar Test

Mode Pair	P-Value	Significance
Public Transport - Private Vehicle	0.0000138	Significant
Public Transport - Non-Motorized Vehicle	0.0119	Significant
Private Vehicle - Non-Motorized Vehicle	0.710	Not Significant

The following interpretations and inferences can be drawn from the results and figure above:

1) Significant modal change was observed for Public Transport, as people tended to use it less in post-lockdown setting. As people are prone to view public transport as an unsafe mode due to fear of contagion, this change is coherent with priori assumptions. Private Vehicles (Private Car, Motorcyle, Ride-Sharing etc.) gained some shares as public transports declined, as people tended to impart safety to private vehicles. Non-Motorized Vehicles (Rickshaw, Cycling, Walking) also gained some shares, as travelers emphasized more

changes on these. Due to this increase, traffic volume and congestions are more prone to incur in new normal situation as less use of public transport and more inclination towards private demand-response vehicles tend to increase congestion and traffic volume (Beaudoin & Lawell, 2017).

2) Significant inter-modal shifts were observed from Public Transport to Private Vehicles and vice-versa. Similar observations were made for the case of Public Transport to Non-Motorized Vehicles, as the changes were significant from McNemar Test. This solidifies the idea that travelers definitely are experiencing a shift in their mode choice preferences and are considering new factors while making mode choice decisions. However, mode shift from private vehicles to non-motorized vehicles were not significant, which may signify the fact that travelers viewed both vehicles to be equally safe with similar utilities and thus, may not have required to commit a change in their choices. Thus, the factors that affect their mode choice were needed to be studied further which was done through the mode choice modelling analysis.

6.2.2 Trip Characteristics

Various changes in trip characteristics (frequency, distance, time, and cost) were also observed and were analyzed. The shift in weekly trip frequency was exhibited in **Figure 5-2** and the change in average distance, time, and cost are tabulated in **Table 5-2.** Various understandings were inferred from the results following the figure and table.

Table 6-2. Summary of Average of Trip Characteristics in Pre and Post Setting

Characteristic	Before Lockdown	After Lockdown
Average Travel Time	55.93 Minutes	56.21 Minutes
Average Typical Distance	5.76 Kilometers	5.49 Kilometers
Average Cost of Trip	132 Taka	148 Taka

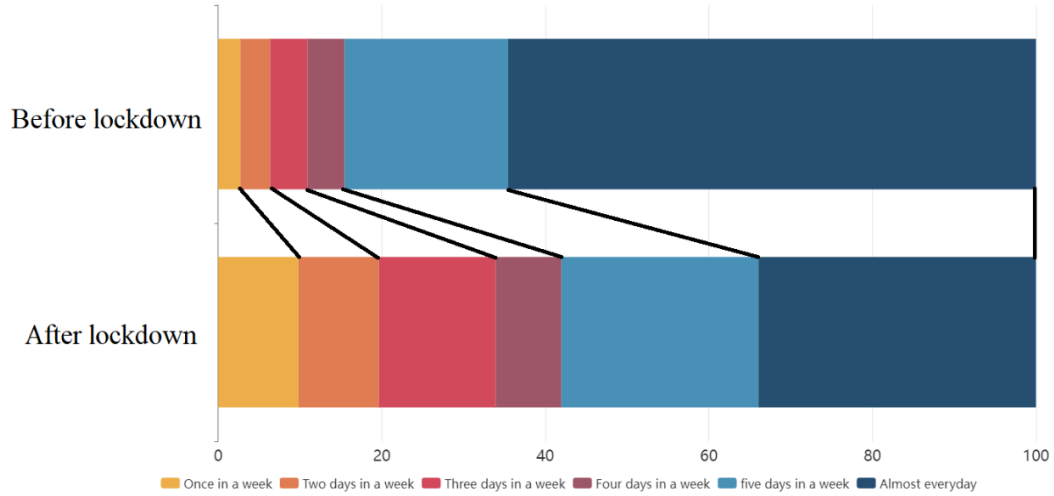


Figure 6-2. Weekly Trip Frequency in Pre and Post Lockdown Setting

The following interpretations and inferences can be drawn from the results and figure above:

1) Average cost of trips has gone up significantly, despite cost of public transports remaining constant. From our previous findings, people shifted from public transports to private ones, leading to this higher cost of travel from these trips. Also, it can also be inferred that, travelers are willing to spend more on modes that ensure their safety and limits contagion.
2) Average typical distance has reduced, which can be interpreted as people are using their modes for shorter distances to reduce exposure time. However, the travel time is still similar in pre and post lockdown setting. Which means, people are travelling less distance for more time. Several factors may have led to this change, such as, congestion, demand-responsive mode usage etc.
3) Frequency of trips have gone down significantly, as portion of trips that were made almost everyday have reduced a lot, while lesser frequencies have increased in their shares. Reasons such as, utilization of Work from Home (WFH) and Online Classes may have impacted this change, while it is also possible that travelers have tried to reduce their exposure outside. Some institutions are still using WFH and online classes in new normalcy and these have been integrated into daily lives of commute and thus, they have significant impact on this change.

6.2.3 Importance Imparted on Various Levels of Service (LOS) and Trip Characteristics

The ranking of the average of these characteristics changed from pre-lockdown to post-lockdown and the importance imparted were significantly changed. The changes along with the results of Wilcoxon Test are summarized in **Figure 6-3** and **Table 6-4.**

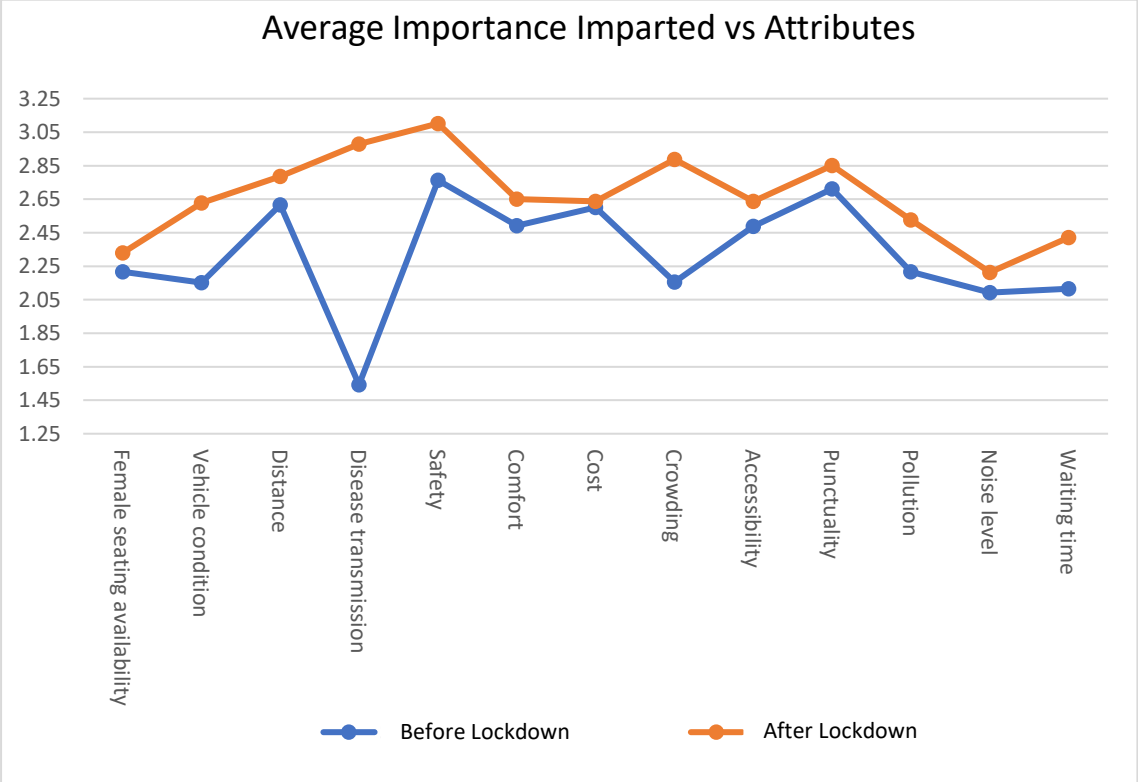


Figure 6-3. Change in Average Importance Imparted on Various Attributes in Pre and Post Lockdown Setting

Table 6-3. Summary of Average of Trip Characteristics in Pre and Post Setting

Characteristic	T-Statistic	P-Value	Significance
Female seating availability	159	0.00139	Non-Significant
Vehicle condition	79500	0.000	Significant
Distance	365	0.000505	Significant
Fear of Disease transmission	57500	0.000	Significant
Safety	212	0.000	Significant
Comfort	611.5	0.00121	Significant
Cost	1390.5	0.70051	Non-Significant
Crowding	468.5	0.000	Significant
Accessibility	353.5	0.000562	Significant

Table 6-3 ***(continued)***

Punctuality	194.5	0.000470	Significant
Pollution	135	0.000	Significant
Noise level	159	0.000228	Significant
Waiting time	221	0.000	Significant

The following interpretations and inferences can be drawn from the results and figure above:

1) Vehicle & Personal Safety, Punctuality of Mode (matching expected travel time) and Trip Distance were the top three factors that travelers provided emphasis on while making a mode choice decision in pre-lockdown era. This signifies the fact that travelers tended to prioritize their safety above anything and along with time of travel. The averages were very similar to each other, and it could be said that they were prioritized somewhat equally. Waiting time, Noise Level and Fear of Disease ranked the lowest, showing the fact that people tended to overlook these factors while choosing a mode and were very indifferent towards any change of these factors.

2) However, in post-lockdown setting Vehicle & Personal Safety still were the most important, while a significant shift led to fear of disease transmission and crowding to be an important factor while choosing mode. This coincides with our assumption that safety and distancing related factors are significantly more important now than ever, as people avoided transports that were crowded and deemed unsafe. Waiting Time, Female Seating Availability and Noise Level ranked the lowest, meaning that people are no longer prioritizing these factors and are indifferent of whether or not these factors vary in level. Thus, it can be said that Level of Service attributes are being prioritized less, while safety and distancing related variables are being emphasized more. We can also see a significant downward shift in trip related attributes, meaning people are less inclined towards cost, time and distance to influence their mode choice behavior.

3) The change in importance of the factors showcase some drastic changes as most changes were significant and various high climbs and drops were observed.

However, Female Seating Availability and Cost of Trip did not undergo any significant shift in their outcomes. It can be inferred that these two factors are similar in both before and after lockdown settings and similar importance are inferred on these two factors. Both factors were moderately middling in their ranks, meaning, that they are moderately important in influencing mode choice behavior. However, as this test was non-parametric, it does not consider all the complex relationship between variables while measuring the changes and thus, are likely to be narrowed. Furthermore, it does not provide insights on expected changes and interaction between the changes. Thus, parametric evaluation and comparative analysis was required which was done in the next section.

6.3 Changes in the Impact of Mode Choice Factors

The changes of the impact of mode choice factors were identified and the significance of the changes were determined. The pre-lockdown model acted as the base of comparison and the coefficients of the post-lockdown model were checked against it. Level of Significance less than 0.1 was considered as significant. Public Transport (PT) was used as the reference category of mode and the other transports were compared against it. Interaction model was constructed to cross-validate the changes from comparing the two models to eliminate the effects of heterogeneous external factors. The summary of the impacts and the change in impacts of the variables are summarised in **Table 5-1 and 5-2**.

Table 6-4. Summary of the Impacts and Changes in Impacts of the Variables for Choosing Private Vehicle (PV) Over Public Transport (PT)

Factor Name	Correlation With Pre-Lockdown Decision Making	Correlation With Post-Lockdown Decision Making	Slope Change Between Two Models
Gender	Not Significant	Not Significant	+0.4171
Age	Positively Correlated	Not Significant	-1.4099
Number of Adults in HH	Not Significant	Not Significant	Not Significant
Number of Children in HH	Not Significant	Not Significant	Not Significant

Table 6-4. ***(continued)***

Factor Name	Correlation With Pre-Lockdown Decision Making	Correlation With Post-Lockdown Decision Making	Slope Change Between Two Models
Ownership of Residence	Not Significant	Not Significant	Not Significant
Type of Residence	Not Significant	Not Significant	Not Significant
Number of Motorcycles Owned by HH	Positively Correlated	Positively Correlated	+0.216
Number of Private Cars Owned by HH	Not Significant	Negatively Correlated	Not Significant
Monthly Income Range of Household	Not Significant	Positively Correlated	+0.4392
Level of Education	Not Significant	Not Significant	Not Significant
Employment Status	Negatively Correlated	Not Significant	+0.8114
Number of Days Mode Used in a Week	Not Significant	Negatively Correlated	Not Significant
Number of Times Mode Used in a Day	Positively Correlated	Not Significant	Not Significant
Distance Travelled by Mode in Most Frequented Trip	Negatively Correlated	Not Significant	-0.1938
Cost incurred on Most Frequented Trip	Positively Correlated	Not Significant	-0.4603
Travel Time for a Single Trip	Negatively Correlated	Negatively Correlated	Not Significant
Purpose of Most Frequented Trip	Positively Correlated	Not Significant	Not Significant
External Attributes of Mode	Not Significant	Not Significant	+0.2882
Safety & Distancing in Mode	Positively Correlated	Positively Correlated	+0.5303
Trip Related Attributes	Not Significant	Not Significant	-0.2072

Table 6-5. Summary of the Impacts and Changes in Impacts of the Variables for Choosing Non-Motorized Vehicle (NMV) Over Public Transport (PT)

Factor Name	Correlation With Pre-Lockdown Decision Making	Correlation With Post-Lockdown Decision Making	Slope Change Between Two Models
Gender	Positively Correlated	Not Significant	-0.2534
Age	Positively Correlated	Not Significant	Not Significant
Number of Adults in HH	Not Significant	Not Significant	Not Significant
Number of Children in HH	Negatively Correlated	Not Significant	+0.1036
Ownership of Residence	Positively Correlated	Positively Correlated	Not Significant
Type of Residence	Not Significant	Not Significant	Not Significant
Number of Motorcycles Owned by HH	Not Significant	Positively Correlated	Not Significant
Number of Private Cars Owned by HH	Positively Correlated	Positively Correlated	Not Significant
Monthly Income Range of Household	Not Significant	Positively Correlated	+0.4033
Level of Education	Not Significant	Not Significant	Not Significant
Employment Status	Not Significant	Positively Correlated	Not Significant
Number of Days Mode Used in a Week	Negatively Correlated	Not Significant	Not Significant
Number of Times Mode Used in a Day	Positively Correlated	Not Significant	-0.21
Distance Travelled by Mode in Most Frequented Trip	Not Significant	Not Significant	-0.0125
Cost incurred on Most Frequented Trip	Positively Correlated	Positively Correlated	+0.049
Travel Time for a Single Trip	Negatively Correlated	Not Significant	+0.5640
Purpose of Most Frequented Trip	Not Significant	Not Significant	Not Significant

Table 6-5. ***(continued)***

Factor Name	Correlation With Pre-Lockdown Decision Making	Correlation With Post-Lockdown Decision Making	Slope Change Between Two Models
External Attributes of Mode	Positively Correlated	Not Significant	-0.3371
Safety & Distancing in Mode	Positively Correlated	Positively Correlated	+0.2219
Trip Related Attributes	Not Significant	Negatively Correlated	-0.3226

6.4 Discussion

The following interpretations and understandings are stemmed from the results obtained above.

6.4.1 Private Vehicles (PV) in Post-Lockdown

1) Effects of Gender were significant in neither pre-lockdown nor post-lockdown periods. However, positive significant changes were observed from interaction testing. This can be explained by the fact that multinomial logit models tend to fit data for best likelihood estimates than treating each variable individually. Thus, the gender parameter was regularized heavily leading to moderate effect on final model but on a comparison basis the changes were significantly modifying the impact. The positive change indicates that the variable was more important in post-lockdown setting, that is, women prefer private vehicles more in post-lockdown setting departing from public transports and transit services.

2) Age of the respondents were significant in pre-lockdown setting but were not significant any longer in post-lockdown setting. The change was further backed by the interaction test, that exhibited a negative slope change, denoting the fact that impact of age on choosing private vehicles as mode for trips were less significant in post lockdown settings. Thus, people of all ages were likely to use private vehicles equally as public transport.

3) Number of Motorcycles owned by HH was positively impactful in both time period. That infers that with the increase of number of motorcycles, the mode choice are more prone to skewing towards private vehicle than public transport.

The change of impact was also positively significant, denoting that it was more important than before in impacting mode choice decision.

4) Number of private cars owned by HH was not significant in pre-lockdown setting and was negatively correlated with the outcome in post-lockdown setting. This result was not coherent with priori assumptions that number of private cars would increase chances of using private vehicles more. This can be explained by the fact the logit model tries to fit over all variables for best fit of outputs and thus, this variable got incorrectly regularized. However, it is also possible that the measurement of the variable was incorrect by random effects and thus, further study on this aspect is required for confirmation.

5) Monthly Income of Household was not significant in choosing private vehicles over public transport in pre-lockdown setting but was significant in post-lockdown setting. It is further backed by the interaction analysis that showed that the change was significant. This means, travelers are more likely to prioritize their monthly income as a factor while choosing modes. As, COVID-19 impacted the livelihood of countless families globally, the lowering of their income may result in them shifting to public transport, despite safety concerns.

6) Employment Status of the travelers were negatively correlated in pre-pandemic situation, meaning student/unemployed travelers preferred private vehicles more and employed/self-employed preferred public transport more. However, in post-lockdown situation, the effect of such were nullified as people of all employment status were equally likely to prefer private vehicle over public transport. This change is also signified by the interaction analysis, as the slope levelled towards horizontal. Thus, public transports need to provide better facilities to encourage students and unemployed into using public transport for their daily use.

7) Number of Days the mode is used in a week was not significant in pre-lockdown but was negatively correlated in post-lockdown setting. This may mean that people are more likely to use public transport if they expect to get out more every week. However, the change was not significant from interaction analysis, thus the interpretation can be ignored.

8) Number of times mode is used in a day was significant in pre-COVID situation, which encourages the interpretation that people tend to prefer private vehicles more if they expect to make the trip more daily. As only one-way trips were considered, it can be expected that making the same trip frequently on a same day led to higher usage of private vehicle. Alternatingly, the importance was less significant in post-COVID situation. But the change was not significant, thus the former interpretation can be considered valid in post-lockdown situation as well.

9) A surprising change was observed in case of distance of trips, where in pre-COVID situation travelers preferred public transport whenever the trip was long spatially, but it was no longer significant in post-lockdown setting, the change in which is also validated by interaction analysis. This means, people are providing less emphasis on expected distance of trip while choosing vehicles and may not consider this variable at all while making a mode choice decision.

10) Similar behavior is observed towards cost of trip variable, where in pre-covid setting higher costs were associated with private vehicle choice but were not significant any longer. Hence, it can be inferred that people are prioritizing these trip-related variables less and providing more emphasis on safety and distancing related attributes of the modes.

11) Travel Time were negatively correlated in both periods, confirming the fact that public transports were likely to incur temporally longer trips. There were no significant change in the variable, thus, people still expect buses and human haulers to take longer and if they are short on time may still prefer PV. Thus, if travel times of PT are possible to be reduced, then people will shift more towards public transport.

12) Purpose of the trip was positively correlated in pre-covid time, meaning that people preferred public transport for recurring-purpose based trips such as education, work and children's education or care and preferred private vehicles for shopping, social functions or other less recurring purposes. The post-lockdown model however imparted a non-significant role to this variable, but

the change was not significant, thus, the previous interpretation still holds true and can be considered for post-lockdown situation as well.

13) Importance imparted on external attributes of modes (Vehicle Condition, timeliness, female seating condition etc.) were found to be not significant in both cases. The change was significant, however, as the both cases were non-significant, this change incurs no impact on outcome

14) In a surprising change, Safety & Distancing in mode related latent factor had an increase in importance imparted on to it while choosing private vehicle over public transport. This means people are more concerned about their safety, possible contagion and crowding within the vehicle, thus leading to choose private vehicles. If public transports import more sense of safety to the travelers regarding both personal and COVID-19 safety, then people will prioritize public transport again. But failure to do so will result in more reliance on private transports and lead to more congestions.

15) Effects similar to Gender were observed in case of Trip Related Attributes. As this latent factor contained variables delineating importance imparted on Trip Distance, Cost, Comfort while making mode choice, the cumulative effect of these variables were minimized but comparatively were less important in post-lockdown setting.

16) Number of Adults and Children in HH (collectively household size), Ownership Status of Residence, Type of Residence, Education Level of Travelers were not any significant parameters in changing the choice of modes in any time period at all. It is advisable that they be removed from consideration for future works in post-COVID situation for private vehicles and public transport pairs.

6.4.2 Non-Motorized Vehicles (NMV) in Post-Lockdown

1) Effects of Gender were positively correlated in pre-covid time, meaning, travelers preferred to walk or take rickshaws if they were female. However, the correlation became non-significant in post-lockdown situation and the change was significant at 90% level of significance. Thus, it can be inferred that this

was no longer a factor in post-lockdown situation and all genders can be expect to be equally likely to choose NMV or PT.

2) Impact of Age was deemed to be positively correlated with the choice of NMV over PT by the pre-lockdown model, meaning that older travelers preferred NMV over PT and younger generations still prioritized PT over NMV. The post-lockdown model did not incorporate the effect of age on mode choice, however, this change was not significant according to the interaction model. Thus, the former can still be considered to be valid and older population can be expected to use PT in post-lockdown Dhaka.

3) Number of Children in HH was negatively correlated in pre-lockdown model but was deemed to be non-significant in post-lockdown model. The change was significant, retaining the understanding that people are equally likely to use NMV and PT, regardless of children.

4) Ownership of Residence was a major determining factor in shifting mode choice from PT to NMV, as people owning their place of residence were more likely to use NMV. It is significant in both cases, emphasizing the fact that people with their own residential units are likely to use NMV in the same route as PT. This interesting effect needs more studying to give a proper response as it is a unique outcome with various other spatial, temporal and psychological aspects affecting it.

5) Number of Motorcycles Owned by HH and Employment Status were deemed to be positively correlated as compared to non-significant attribute in pre-lockdown model. But, the change was not significant, thus, implying that the impact of these variables is not significant at all in either case.

6) Number of Private Cars Owned by HH was positively correlated in both periods, but this is counterintuitive as owning private cars can not contribute towards using NMV. This effect needs to be further investigated for external factors that may explain the relationship between such.

7) Monthly Income of Household was not significant in choosing NMV over public transport in pre-lockdown setting but was significant in post-lockdown

setting. It is further backed by the interaction analysis that showed that the change was significant. This means, travelers are more likely to prioritize their monthly income as a factor while choosing modes. As, COVID-19 impacted the livelihood of countless families globally, the lowering of their income may result in them shifting to public transport, despite safety concerns. This is coherent with the outcome of this variable for private vehicles.

8) Number of Days the mode is used in a week was negatively correlated in pre-lockdown but was not significant in post-lockdown setting. The change was not significant from interaction analysis; thus, the former interpretation can be held constant. This may mean that people are more likely to use public transport if they expect to get out more every week, in both pre and post lockdown settings.

9) Number of times mode is used in a day was significant in pre-COVID situation, which encourages the interpretation that people tend to prefer private vehicles more if they expect to make the trip more daily. As only one-way trips were considered, it can be expected that making the same trip frequently on a same day led to higher usage of private vehicle. Alternatingly, the importance was less significant in post-COVID situation. This change was significant in interaction analysis, implying the fact that this is not the case anymore and people choose NMV regardless of number of times they may use it in a day.

10) Distance travelled by mode was not significant in any case, despite having a significant change. A negative change implies that people are prioritizing distance less while choosing NMV over PT.

11) Cost of travel was a significant factor in both post and pre lockdown setting, while a significant positive change is also observed. It means people are prioritizing cost of travel even more while making mode choice decisions and higher costs may lead them to use NMV instead of PT.

12) Travel time was negatively correlated in pre-covid situation but was not significant in post-lockdown and the change was significant. Thus, it can be implied that travel time is no longer a factor and people may prioritize other factors over travel time while choosing a mode.

13) External attributes of modes were positively correlated and were no longer significant. Meaning, people used to focus on vehicle characteristics, pollution and noise factors while making a mode choice decision but that was not the case in post lockdown setting. Thus, PT can convert more travelers to using the mode despite improvement on their vehicle characteristics.

14) Safety & distancing in mode was imparted very high importance in choosing NMV over PT and the change was even more rising. This implies that people are providing high priority on safety, crowding, distancing and disease transmissibility related factors more than ever and they significantly impact mode choice decision and behavior.

15) Trip related attributes were negatively correlated with a significant change. This implies that travelers imparted less importance on trip related attributes while choosing NMV. This is also validated by less importance imparted on the distance, cost and travel time variables and thus, it is likely that people prefer NMV for variables other than just trip considerations alone and is likely to use NMV over temporally and spatially longer trips. Purpose of trip was not significant either in choosing NMV, thus affirming this interpretation even more.

16) Number of Adults in HH, Type of Residence and Level of Education were not significant factors in either case and may be omitted in future studies.

6.5 Summary

The results showed various changes in mode choice and preferences of travelers, and thus, were analyzed against baselines and previous research. The changes in various variables were checked for significance and possible causes behind such changes were analyzed as well. Thus, it can be concluded that public transport facilities need to improve significantly to cope with the new preferences in the new normal and reduce traffic volume on road. Further conclusions are drawn on the next chapter.

Conclusions and Future Works

7.1 Concluding Remarks

In brief, this study has- (i) identified that there indeed has been a significant change in mode and travel behavior of daily commuters of Dhaka Metropolitan Area in the new normal through non-parametric analysis and (ii) analytically showcased that the impact of the factors affecting mode choice have undergone a drastic shift by modelling mode choice and the change between the periods and hence, accomplishes the two objectives of the thesis.

This study was conducted to examine the travel behavior of the travelers within Dhaka Metropolitan Area before and after the COVID 19 lockdown. To attain the objectives, a three-part online questionnaire was used to collect the data. Socio-demographic characteristics, Most Frequented Mode & Trip Data and Importance Imparted on Various Levels of Service (LOS) and Trip Attributes. Considering the first objective, the thesis obtained the following inferences that, after the lockdowns, respondents prioritized disease transmission, safety, crowding, waiting time etc. Trip related attributes were no longer significant, as travelers preferred to pay more, spend more time on the road but limit exposure. Significant shift in modal preferences were found, with new factors to consider. Women were more likely to prefer Private Car and Non-Motorized Vehicles, while men still preferred public transport. The purpose of the trips shifted significantly, due to intrusion of online class, work from home and exposure of e-commerce. Frequency of trips were significantly reduced as well, thus, travelers preferred to be safer and maintain distancing. In Pre-COVID travelers provided more importance on trip related attributes but were more likely to prefer safety and less crowding over anything. Thus, it can be concluded that there indeed has been significant changes in the mode choice behavior and the change of these impacts need to be studied.

The conclusion of the first objective led to the analysis of the second one, where the study aimed at analyzing the change in impacts of these factors by COVID-19. Based on the first outcome, it could be inferred that there was a change, but which mode choices the impact shifted the travelers to was needed to be analyzed. Thus, with the same data, two mode choice models of pre-lockdown and post-lockdown were estimated, calibrated and the changes of the factors were identified using interaction models. The results concluded that public transport was deemed to be unsafe, mostly by women and older populace. Income range of household and number of vehicles owned also played an important role, as they decided who would use public transport and who would use private vehicles. People provided less emphasis on trip related attributes, but still preferred public transport for more recurring trips. Vehicle attributes were not important either, rather they preferred vehicles that had less crowding, maintained distancing and cleanliness. For non-motorized vehicle, similar trends were observed, however, for longer distance and time taken for travel, people preferred public transport. Number of children at their homes were also important as they wanted to keep children safe and used non-motorized vehicle more often. However, majority of users shifted from public transport to other modes, leading to more traffic volume which is exhibited in current situations.

7.2 Research Contribution

The thesis presents several novel findings regarding various changes in mode choice behavior that have the potential to provide new insights on how the behavior of travelers have changed and what new considerations are needed for planning in new normalcy. The following are the main contributions of this research:

1) Identifying the status quo of transportation mode choice of Dhaka Metropolitan Area in the new normal situation

2) Interpreting new changes in mode choice, travel behavior and priorities of travelers to account for in new transportation project planning

3) Introducing a novel technique to compare between impacts of mode choice factors in two different time periods

4) Predict potential changes for a new lockdown/pandemic situation, if one may arise in the new future, which will help the transportation systems to adopt.

7.3 Recommendation

The thesis analyzed the data based on public transport, as no significant shift was observed for shift between private vehicles and non-motorized vehicles in the new normal situation. Thus, the study suggests that public transports need to be made safer and proper distancing and safety precautions need to be installed to improve travelers' attitude towards public transport. Intrusion of motorized private vehicles and non-motorized vehicles have increased congestion by manifold and caused gridlocks over the transportation network. To avoid such, there is no better alternative than public transport. New Mass Rapid Transit (MRT) and Bus Rapid Transit (BRT) projects need to take this into consideration to be a success. Higher cost of travel, accessibility, distance and waiting time were not significant for users, thus, at higher cost, the transport authorities can definitely install safety measures to keep higher proportion of users. Finally, major roads need to be access controlled, as non-motorized vehicles are preferred more on the same route than public transport, leading to speed differential which causes massive issues on multiple aspects.

7.4 Limitations & Future Research

This study has some methodological faults. Because the questionnaire was written in English, it is likely that only individuals who could understand the language completed it. Due to the need for social distance, an online questionnaire was selected over in-person interviews. However, only those with Internet connection were able to complete the questionnaire, which may have led to skewed results. Due to the diminished participation of senior citizens on social media, the sample may have been skewed toward the younger demographic. In addition, it is recommended to conduct additional study on mode selection behavior using larger representative samples.

This study is based on the findings of a questionnaire survey conducted in the city of Dhaka. However, it is expected that the published findings may be applicable to other cities with comparable sociodemographic and economic features, and wherever analogous travel patterns and mode choices exist (e.g., cities in South Asian countries including India, Pakistan, Afghanistan, and Sri Lanka). There may be some similarities with cities in developed countries; nevertheless, caution is advised when projecting these results to such cities, and comparative research is welcomed. Since the sample is biased toward younger and better educated persons, the results should only be

generalized to groups with comparable characteristics. The conclusions presented here may not apply to cities with diversified transit options. In addition, the scale of the pandemic must be considered when extrapolating the results of this study.

The methods adopted by the research are novel in the sense that, the time periods were not considered before and the direct comparison between the two periods were not conducted either. Thus, this method can be explored further and the use of this method can be expanded into various pre and post pandemic researches. The result of the research can also be extrapolated for near future or new lockdown conditions. However, the mode choice models only considered linear relationship between variables, whereas their relationship are far more complex and inter-related. Such complex relationships and consideration of trip-chaining are necessary for future research. As the modes were considered for same trip on same route, trip-chaining could be a valuable add on to future research.

REFERENCES

Abdullah, M., Dias, C., Muley, D., & Shahin, Md. (2020). Exploring the impacts of COVID-19 on travel behavior and mode preferences. *Transportation Research Interdisciplinary Perspectives*, *8*, 100255. https://doi.org/10.1016/j.trip.2020.100255

Abdullah, Md. S., Nowreen, S., Uz Zzaman, R., Hasnat, S., Satu, S. M., & Chowdhury, Md. E. (2021). Urbanising Delta: What Lessons Dhaka Offers to Face Challenges. *Journal of Policy & Governance*, *01*(02), 1–21. https://doi.org/10.33002/jpg010201

Abu-Rayash, A., & Dincer, I. (2020). Analysis of mobility trends during the COVID-19 coronavirus pandemic: Exploring the impacts on global aviation and travel in selected cities. *Energy Research & Social Science*, *68*, 101693. https://doi.org/10.1016/j.erss.2020.101693

Ahasan, R., & Kabir, A. (2019). Performance Evaluation of Public Transportation System: Analyzing the Case of Dhaka, Bangladesh. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3560667

Aloi, A., Alonso, B., Benavente, J., Cordera, R., Echániz, E., González, F., Ladisa, C., Lezama-Romanelli, R., López-Parra, Á., Mazzei, V., Perrucci, L., Prieto-Quintana, D., Rodríguez, A., & Sañudo, R. (2020). Effects of the COVID-19 Lockdown on Urban Mobility: Empirical Evidence from the City of Santander (Spain). *Sustainability*, *12*(9), 3870. https://doi.org/10.3390/su12093870

Arellana, J., Márquez, L., & Cantillo, V. (2020). COVID-19 Outbreak in Colombia: An Analysis of Its Impacts on Transport Systems. *Journal of Advanced Transportation*, *2020*, 1–16. https://doi.org/10.1155/2020/8867316

Aydin, N., Kuşakcı, A. O., & Deveci, M. (2022). The impacts of COVID-19 on travel behavior and initial perception of public transport measures in Istanbul. *Decision Analytics Journal*, *2*, 100029. https://doi.org/10.1016/j.dajour.2022.100029

Baig, F., Kirytopoulos, K., Lee, J., Tsamilis, E., Mao, R., & Ntzeremes, P. (2022). Changes in People's Mobility Behavior in Greece after the COVID-19 Outbreak. *Sustainability*, *14*(6), 3567. https://doi.org/10.3390/su14063567

Bangladesh Road Transport Authority. (2022). *সারা বাংলাদেশে মোটরযান নিবন্ধনের সংখ্যা.* http://www.brta.gov.bd/site/page/74b2a5c3-60cb-4d3c-a699-e2988fed84b2/Number-of-registered-Vehicles-in-Whole-BD

Beaudoin, J., & Lawell, C.-Y. C. L. (2017). The Effects of Urban Public Transit Investment on Traffic Congestion and Air Quality. In H. Yaghoubi (Ed.), *Urban Transport Systems*. IntechOpen. https://doi.org/10.5772/66834

Beck, M. J., & Hensher, D. A. (2020). Insights into the impact of COVID-19 on household travel and activities in Australia – The early days of easing restrictions. *Transport Policy*, *99*, 95–119. https://doi.org/10.1016/j.tranpol.2020.08.004

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press.

Bhaduri, E., Manoj, B. S., Wadud, Z., Goswami, A. K., & Choudhury, C. F. (2020). Modelling the effects of COVID-19 on travel mode choice behaviour in India. *Transportation Research Interdisciplinary Perspectives*, *8*, 100273. https://doi.org/10.1016/j.trip.2020.100273

Campisi, T., Canale, A., & Tesoriere, G. (2019). The development of walkability in the historic centre of Enna: the case of the Saint Tommaso neighbourhood. *European Transport Europei, Paper n° 4*, 9.

de Man, J., Campbell, L., Tabana, H., & Wouters, E. (2021). The pandemic of online research in times of COVID-19. *BMJ Open*, *11*(2), e043866. https://doi.org/10.1136/bmjopen-2020-043866

de Vos, J. (2020). The effect of COVID-19 and subsequent social distancing on travel behavior. *Transportation Research Interdisciplinary Perspectives*, *5*, 100121. https://doi.org/10.1016/j.trip.2020.100121

Enam, A. (2010). *Developing a Comprehensive Mode Choice Model to capture the Preferences for Mass Rapid Transit in Dhaka* [M.Sc. Thesis, Bangladesh University of Engineering and Technology (BUET)]. http://lib.buet.ac.bd:8080/xmlui/handle/123456789/379

Enam, A., & Choudhury, C. F. (2011). Methodological Issues in Developing Mode Choice Models for Dhaka, Bangladesh. *Transportation Research Record: Journal of the Transportation Research Board*, *2239*(1), 84–92. https://doi.org/10.3141/2239-10

Fisher, R. A. (1926). The Arrangement of Field Experiments. *Journal of the Ministry of Agriculture*, *33*, 503–515.

IEA. (2020). *Global Energy Review 2020*. https://www.iea.org/reports/global-energy-review-2020

Iseki, H., & Taylor, B. (2010). Style versus Service? An Analysis of User Perceptions of Transit Stops and Stations. *Journal of Public Transportation*, *13*(3), 23–48. https://doi.org/10.5038/2375-0901.13.3.2

Jamal, S., Chowdhury, S., & Newbold, K. B. (2022a). Transport preferences and dilemmas in the post-lockdown (COVID-19) period: Findings from a qualitative study of young commuters in Dhaka, Bangladesh. *Case Studies on Transport Policy*, *10*(1), 406–416. https://doi.org/10.1016/j.cstp.2022.01.001

Jamal, S., Chowdhury, S., & Newbold, K. B. (2022b). COVID-19 and Modal Shift towards Motorized Two-wheelers in Dhaka, Bangladesh. *Findings*. https://doi.org/10.32866/001c.33830

Jamal, S., & Paez, A. (2020). Changes in Trip-making Frequency by Mode during COVID-19. *Findings*. https://doi.org/10.32866/001c.17977

Koppelman, F. S., & Bhat, C. R. (2006). *A Self Instructing Course in Mode Choice Modeling: Multinomial and Nested Logit Models*.

Koppelman, F. S., & Wen, C.-H. (2000). The paired combinatorial logit model: properties, estimation and application. *Transportation Research Part B: Methodological*, *34*(2), 75–89. https://doi.org/10.1016/S0191-2615(99)00012-0

Marsden, G., & Docherty, I. (2021). Mega-disruptions and policy change: Lessons from the mobility sector in response to the Covid-19 pandemic in the UK. *Transport Policy*, *110*, 86–97. https://doi.org/10.1016/j.tranpol.2021.05.015

McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Behavior. In P., Ed. Zarembka (Ed.), *Frontiers in Econometrics* (pp. 105–142). Academic Press.

McFadden, D. (1976). Behavioral Travel Demand Models. In *The Mathematical Theory of Demand Models* (pp. 305–314).

Mcgrew, J. C., & Monroe, C. B. (1993). *An Introduction to Statistical Problem Solving in Geography. Wm. C*. Brown Publishers, Dubuque, Iowa.

Mogaji, E. (2020). Impact of COVID-19 on transportation in Lagos, Nigeria. *Transportation Research Interdisciplinary Perspectives*, *6*, 100154. https://doi.org/10.1016/j.trip.2020.100154

New Age Bangladesh. (2022, February 12). *Educational instts across Bangladesh to reopen after Feb 21: minister*. https://www.newagebd.net/article/162559/educational-instts-across-bangladesh-to-reopen-after-feb-21-minister

Nikiforiadis, A., Ayfantopoulou, G., & Stamelou, A. (2020). Assessing the Impact of COVID-19 on Bike-Sharing Usage: The Case of Thessaloniki, Greece. *Sustainability*, *12*(19), 8215. https://doi.org/10.3390/su12198215

Ozbilen, B., Slagle, K. M., & Akar, G. (2021). Perceived risk of infection while traveling during the COVID-19 pandemic: Insights from Columbus, OH.

Transportation Research Interdisciplinary Perspectives, *10*, 100326. https://doi.org/10.1016/j.trip.2021.100326

Padmanabhan, V., Penmetsa, P., Li, X., Dhondia, F., Dhondia, S., & Parrish, A. (2021). COVID-19 effects on shared-biking in New York, Boston, and Chicago. *Transportation Research Interdisciplinary Perspectives*, *9*, 100282. https://doi.org/10.1016/j.trip.2020.100282

Paul, T., Ornob, A. B. S., Chakraborty, R., & Anwari, N. (2021). Assessment of COVID-19 induced travel pattern changes in Dhaka City. *Case Studies on Transport Policy*, *9*(4), 1943–1955. https://doi.org/10.1016/j.cstp.2021.11.003

Pawar, D. S., Yadav, A. K., Akolekar, N., & Velaga, N. R. (2020). Impact of physical distancing due to novel coronavirus (SARS-CoV-2) on daily travel for work during transition to lockdown. *Transportation Research Interdisciplinary Perspectives*, *7*, 100203. https://doi.org/10.1016/j.trip.2020.100203

Seabold, S., & Perktold, J. (2010). statsmodels: Econometric and statistical modeling with python. *9th Python in Science Conference*.

Shaik, Md. E., Hossain, Q. S., & Rony, G. M. F. F. (2021). Impact of COVID-19 on Public Transportation and Road Safety in Bangladesh. *SN Computer Science*, *2*(6), 453. https://doi.org/10.1007/s42979-021-00849-5

Shakibaei, S., de Jong, G. C., Alpkökin, P., & Rashidi, T. H. (2021). Impact of the COVID-19 pandemic on travel behavior in Istanbul: A panel data analysis. *Sustainable Cities and Society*, *65*, 102619. https://doi.org/10.1016/j.scs.2020.102619

The Daily Star. (2020, September 2). Public Transport: Pre-Covid fare, health rules not followed. *The Daily Star*. Public Transport: Pre-Covid fare, health rules not followed

Tian, H., Liu, Y., Li, Y., Wu, C.-H., Chen, B., Kraemer, M. U. G., Li, B., Cai, J., Xu, B., Yang, Q., Wang, B., Yang, P., Cui, Y., Song, Y., Zheng, P., Wang,

Q., Bjornstad, O. N., Yang, R., Grenfell, B. T., … Dye, C. (2020). An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science*, *368*(6491), 638–642. https://doi.org/10.1126/science.abb6105

Torrisi, V., Campisi, T., Inturri, G., Ignaccolo, M., & Tesoriere, G. (2021). *Continue to share? An overview on italian travel behavior before and after the COVID-19 lockdown*. 090010. https://doi.org/10.1063/5.0048512

Train, K. E. (2001). *Discrete Choice Methods with Simulation*. Cambridge University Press. https://doi.org/10.1017/CBO9780511805271

WHO. (2020, March 11). *WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020*.

Yasmin, F. (2008). *Nested Logit Mode-Choice Model for Office Workers: A Case Study in Dhaka City* [MURP Thesis, Bangladesh University of Engineering & Technology (BUET)]. http://lib.buet.ac.bd:8080/xmlui/handle/123456789/2185

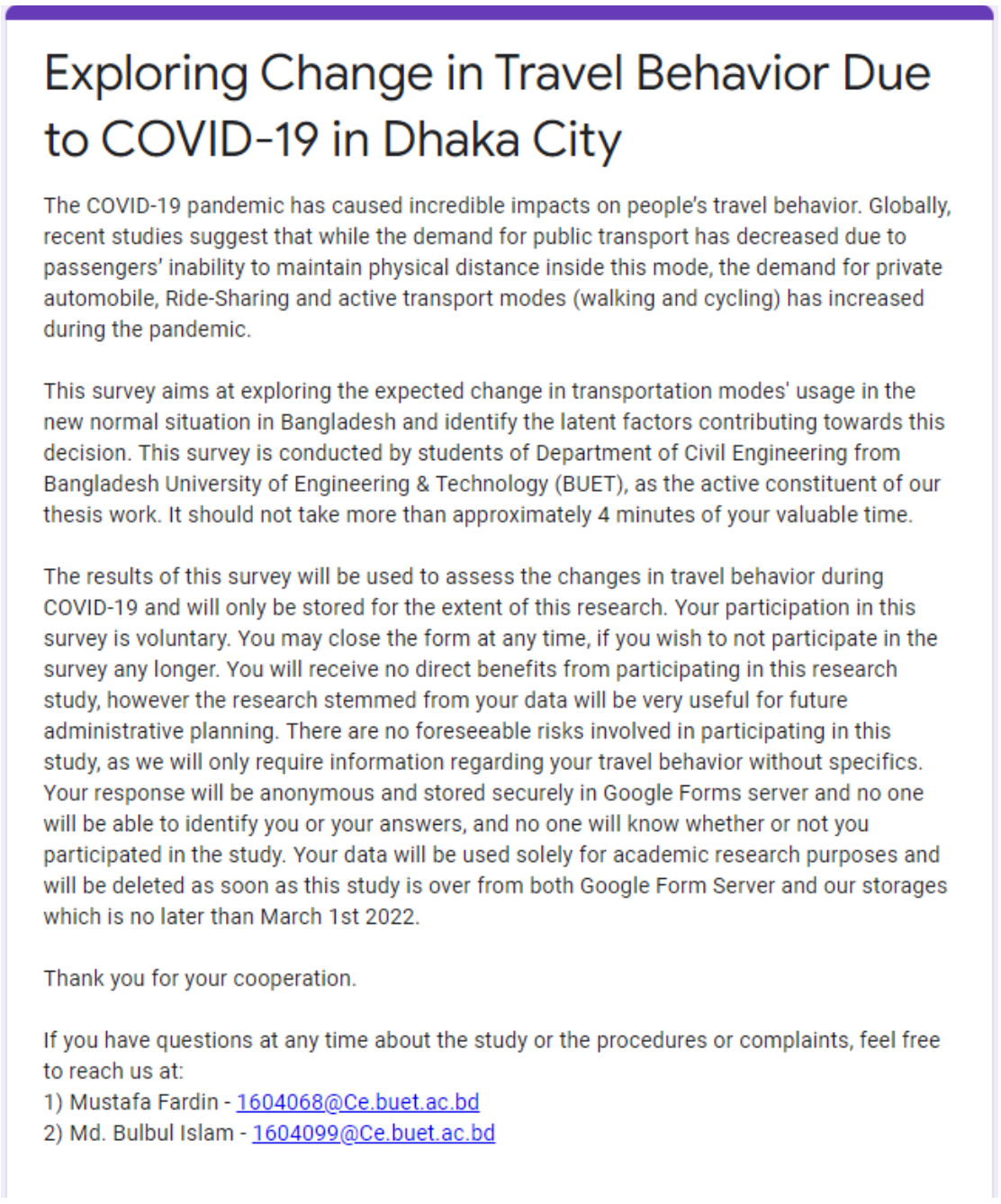
Yasmin, F., Basu, N., & Palash, A. R. (2006). *A Study on Mode Choice Behaviour of Public University Students - Case Study of University of Dhaka* [BURP Thesis]. Bangladesh University of Engineering & Technology (BUET).

Zafri, N. M., Khan, A., Jamal, S., & Alam, B. M. (2021). Impacts of the COVID-19 Pandemic on Active Travel Mode Choice in Bangladesh: A Study from the Perspective of Sustainability and New Normal Situation. *Sustainability*, *13*(12), 6975. https://doi.org/10.3390/su13126975

Zhang, L., Darzi, A., Ghader, S., Pack, M. L., Xiong, C., Yang, M., Sun, Q., Kabiri, A., & Hu, S. (2021). Interactive COVID-19 Mobility Impact and Social Distancing Analysis Platform. *Transportation Research Record: Journal of the Transportation Research Board*, 036119812110438. https://doi.org/10.1177/03611981211043813

APPENDIX

Appendix A



Exploring Change in Travel Behavior Due to COVID-19 in Dhaka City

The COVID-19 pandemic has caused incredible impacts on people's travel behavior. Globally, recent studies suggest that while the demand for public transport has decreased due to passengers' inability to maintain physical distance inside this mode, the demand for private automobile, Ride-Sharing and active transport modes (walking and cycling) has increased during the pandemic.

This survey aims at exploring the expected change in transportation modes' usage in the new normal situation in Bangladesh and identify the latent factors contributing towards this decision. This survey is conducted by students of Department of Civil Engineering from Bangladesh University of Engineering & Technology (BUET), as the active constituent of our thesis work. It should not take more than approximately 4 minutes of your valuable time.

The results of this survey will be used to assess the changes in travel behavior during COVID-19 and will only be stored for the extent of this research. Your participation in this survey is voluntary. You may close the form at any time, if you wish to not participate in the survey any longer. You will receive no direct benefits from participating in this research study, however the research stemmed from your data will be very useful for future administrative planning. There are no foreseeable risks involved in participating in this study, as we will only require information regarding your travel behavior without specifics. Your response will be anonymous and stored securely in Google Forms server and no one will be able to identify you or your answers, and no one will know whether or not you participated in the study. Your data will be used solely for academic research purposes and will be deleted as soon as this study is over from both Google Form Server and our storages which is no later than March 1st 2022.

Thank you for your cooperation.

If you have questions at any time about the study or the procedures or complaints, feel free to reach us at:
1) Mustafa Fardin - 1604068@Ce.buet.ac.bd
2) Md. Bulbul Islam - 1604099@Ce.buet.ac.bd

Figure A-1. Introduction of Form

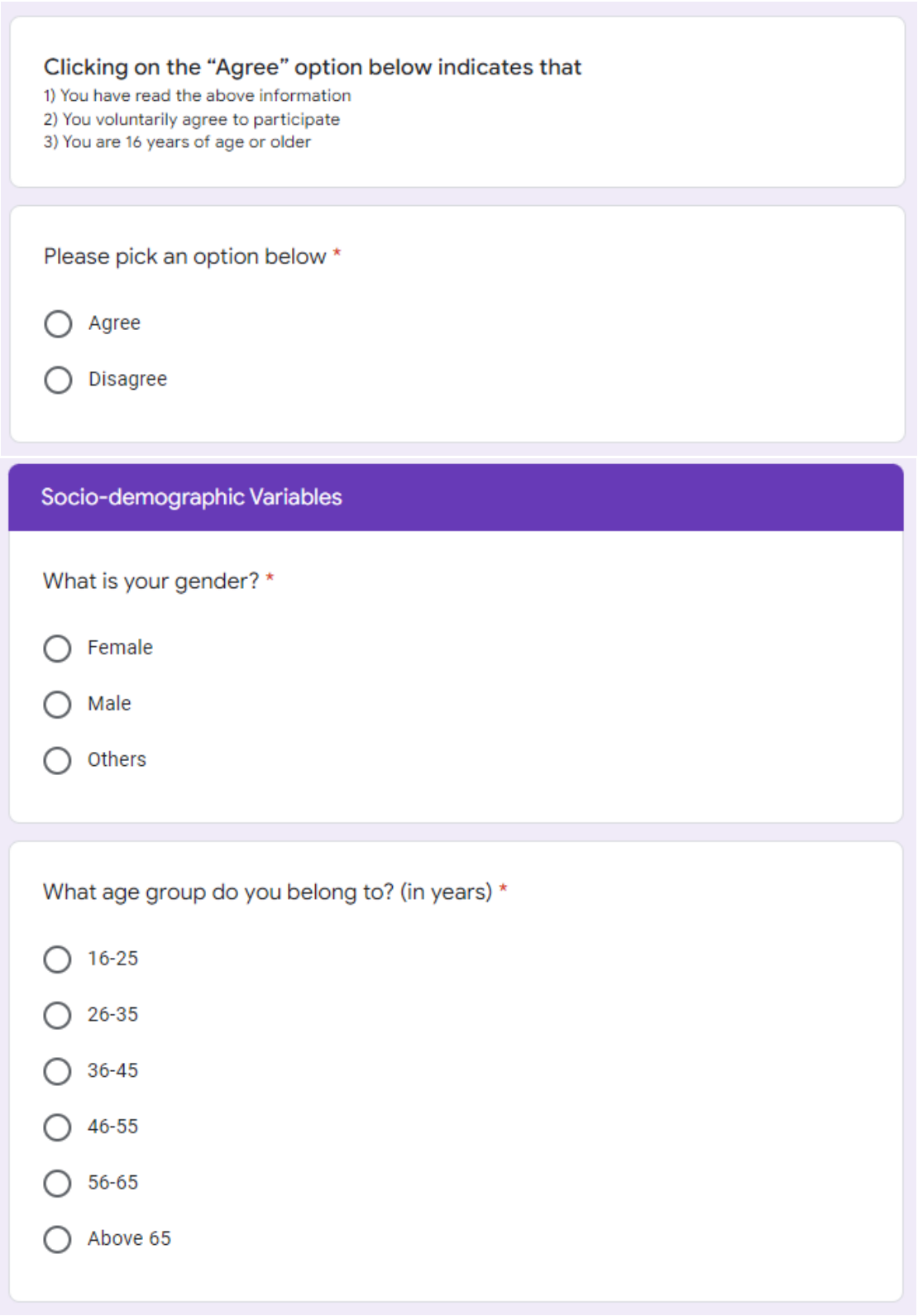


Figure A-2. Confirmation of Disclosure and Socio-Demographic Variable Section start containing Gender and Age Group Questions

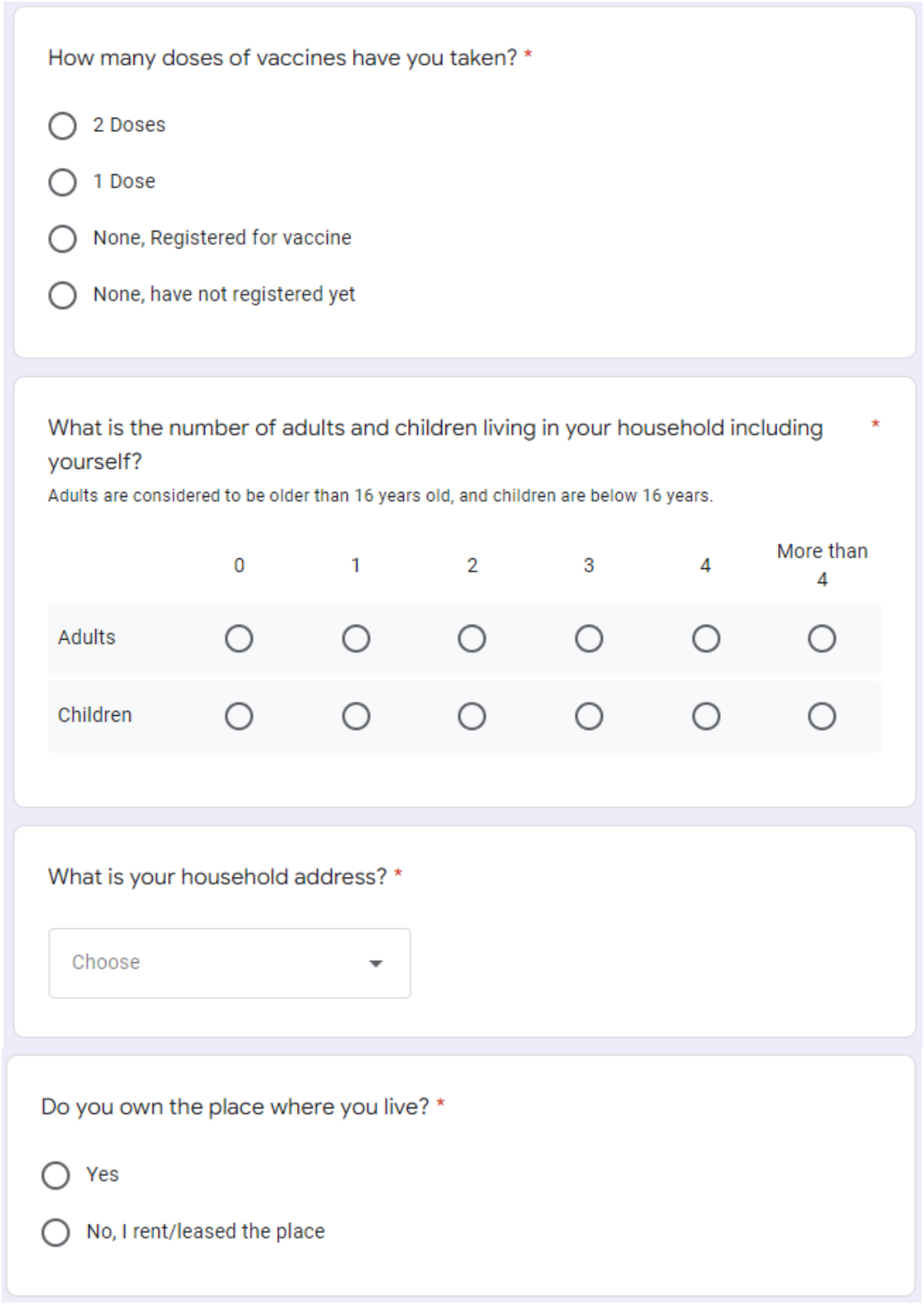


Figure A-3. Socio Demographic Variables (continued) Doses, Household Size, Address and Ownership of Residence

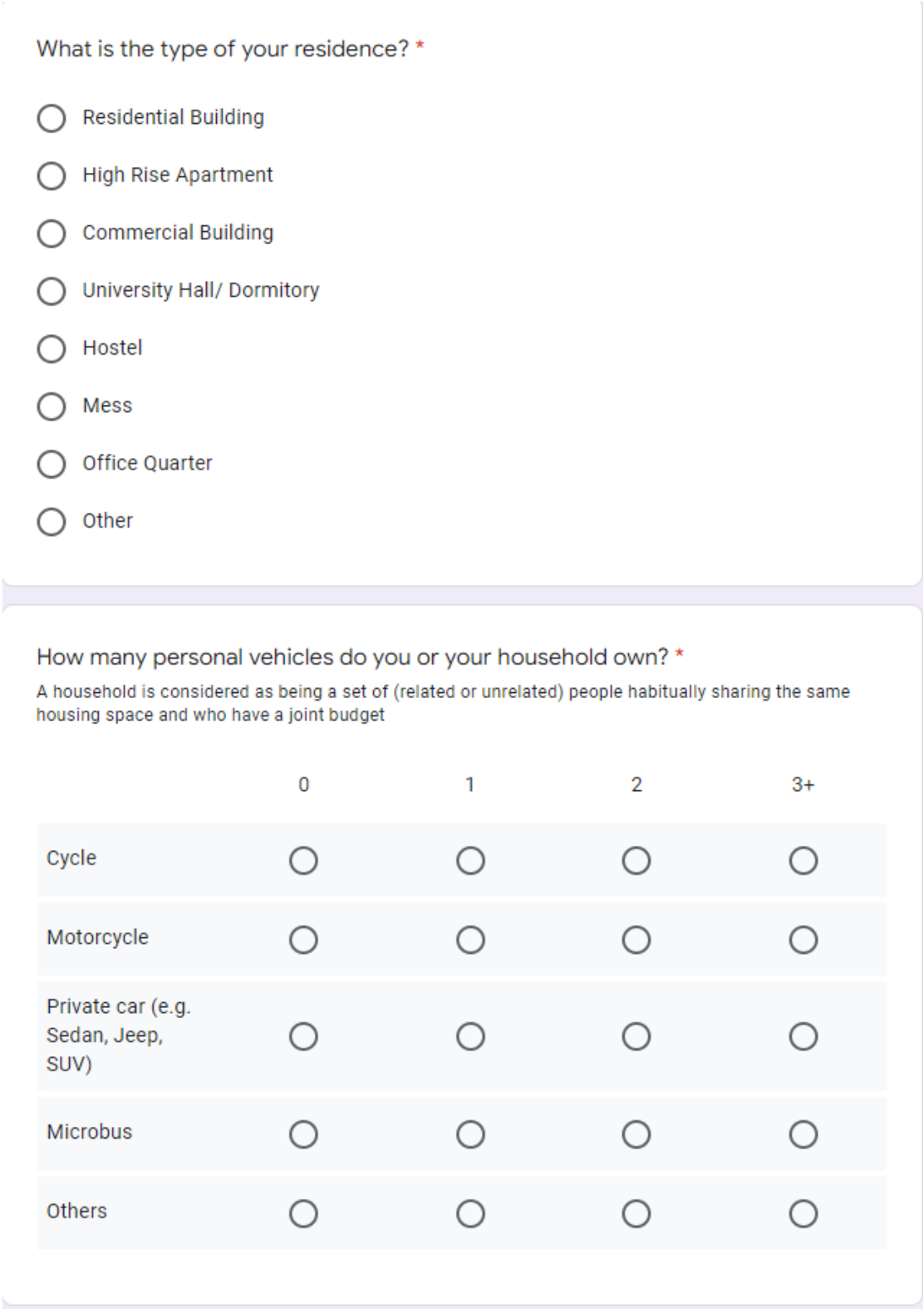


Figure A-4. Socio Demographic Variables (continued) Type of Residence and Vehicles Owned by HH

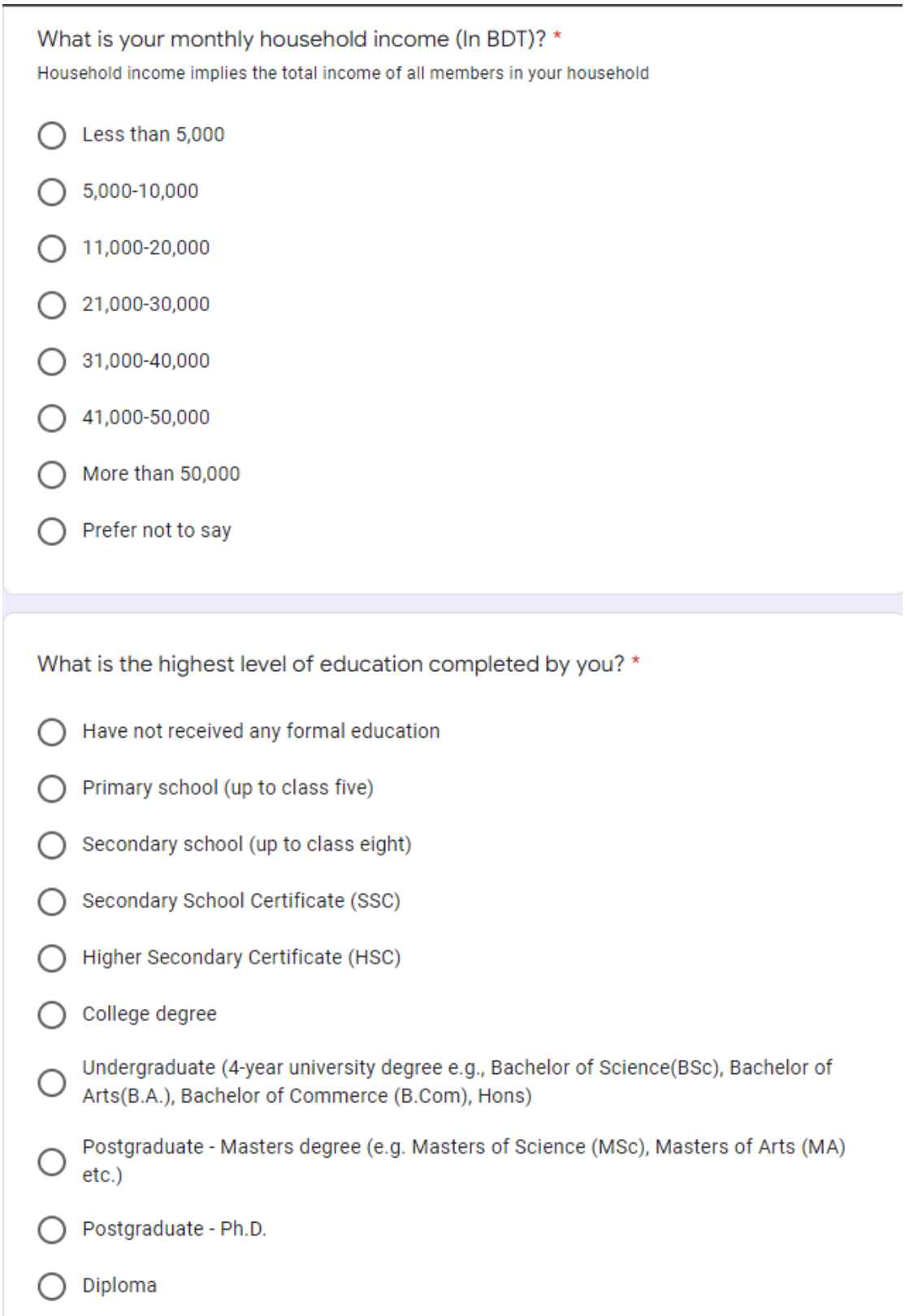


Figure A-5. Socio Demographic Variables (continued) Income Range and Level of Education

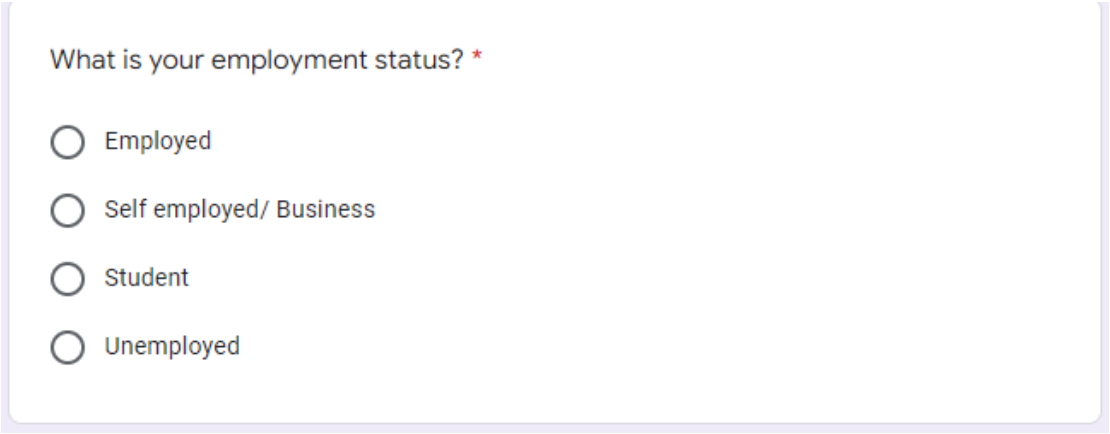


Figure A-6. Socio Demographic Variables (continued) Employment Status

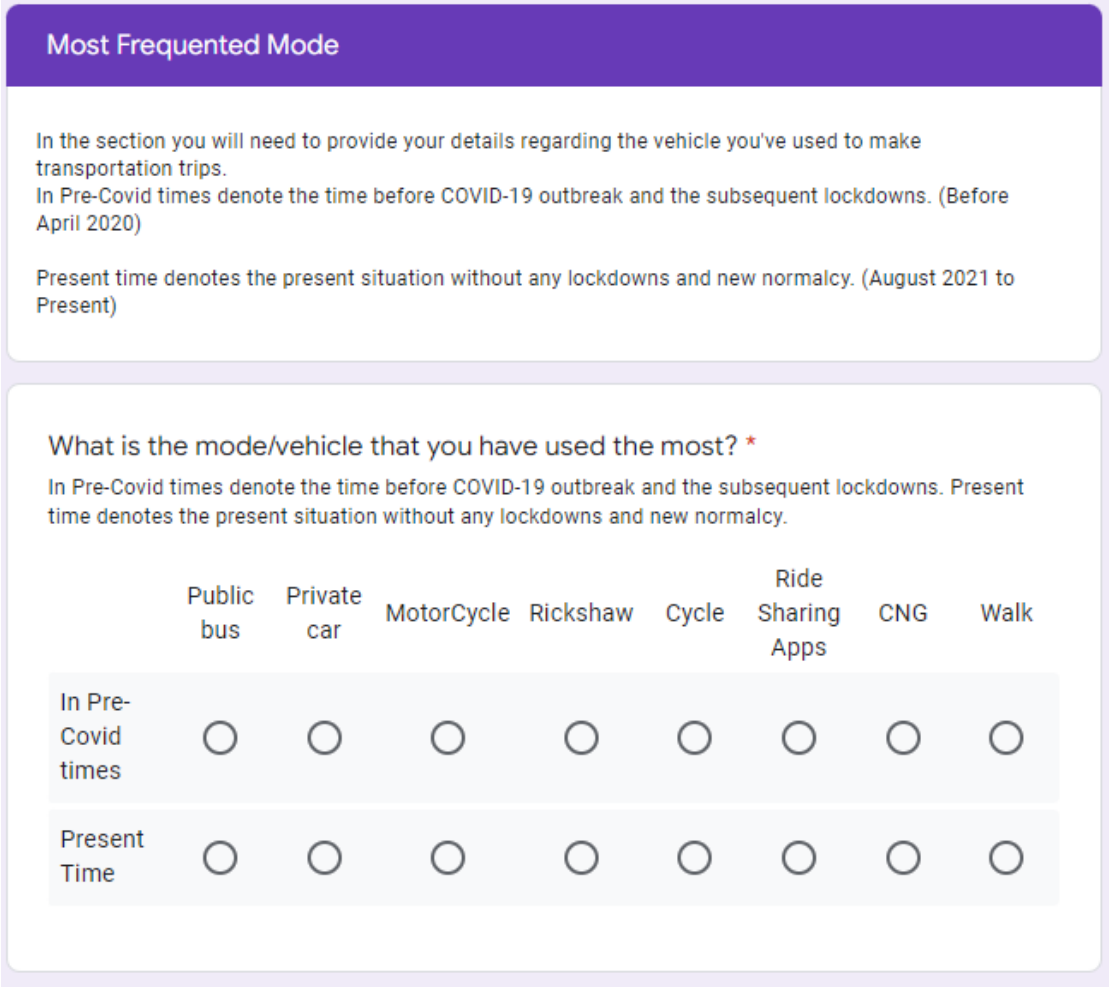


Figure A-7. Start of Most Frequented Mode Section containing Most Frequented Mode Selection

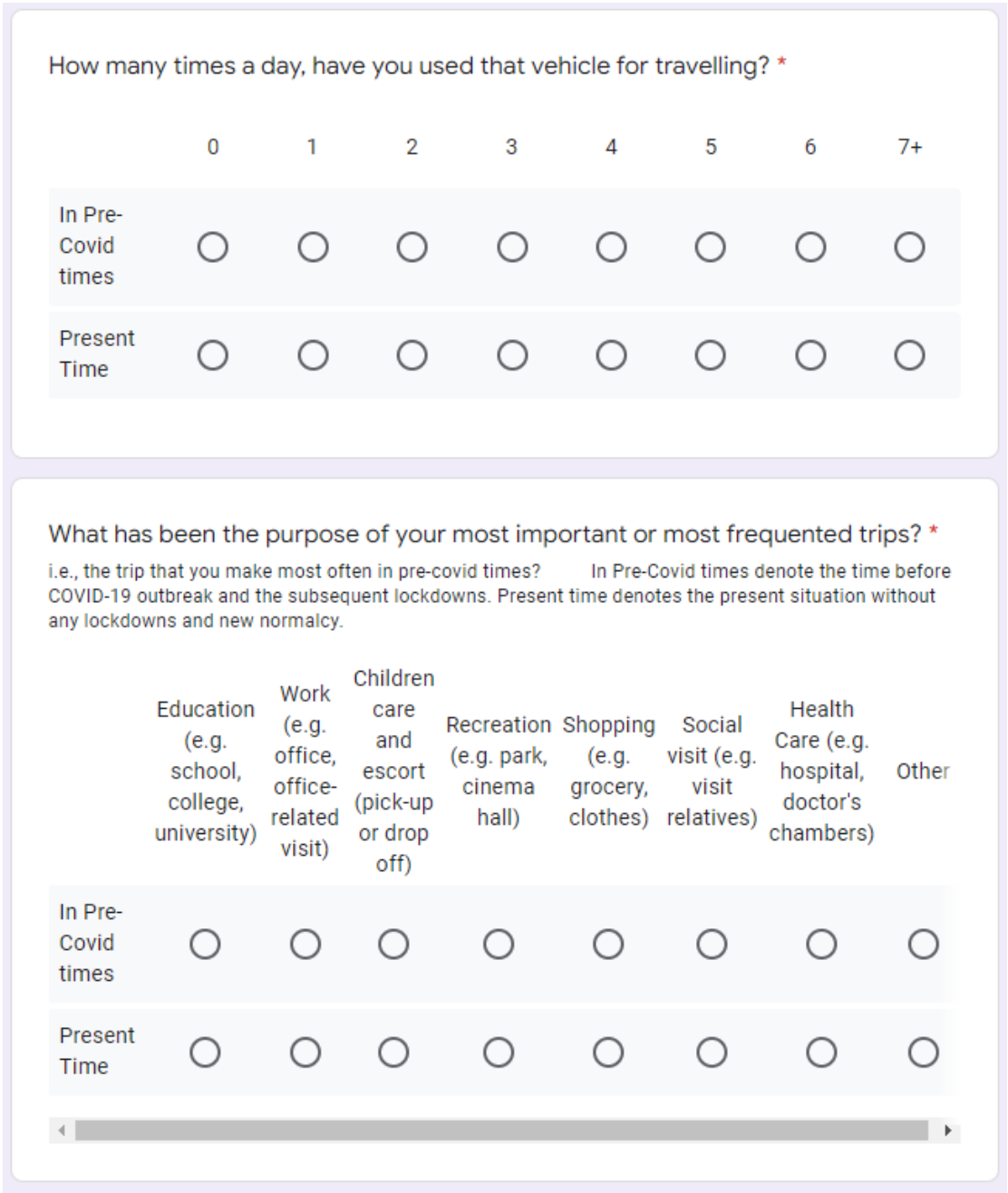


Figure A-8 Most Frequented Mode Section (continued) containing Daily Use and Purpose

How many times have you had to go out weekly? *

i.e. for travel purposes within Dhaka city.

	0	1	2	3	4	5	5+
In Pre-Covid times	○	○	○	○	○	○	○
Present Time	○	○	○	○	○	○	○

What was the typical distance of a single trip in your most used mode/vehicle? *

Distance in a single trip, as in, the distance travelled by you in the mode/vehicle until you got off of it

	less than 2 Kilometers	2 Km - 4 Km	4 Km - 6 Km	6 km - 8 Km	8-10 Km	More than 10 Km
In Pre-Covid times	○	○	○	○	○	○
Present Time	○	○	○	○	○	○

How long does it take for you to travel using that vehicle in one single trip? *

Please provide an approximation of the time it takes for you to move between two points using your most used vehicle

	Less than 30 Minutes	30 mins - 1 hrs	1 - 1.5 hrs	1.5 - 2 hrs	More than 2 hrs
In Pre-Covid times	○	○	○	○	○
Present Time	○	○	○	○	○

Figure A-9. Most Frequented Mode Section (continued) containing weekly use, distance and travel time of trip

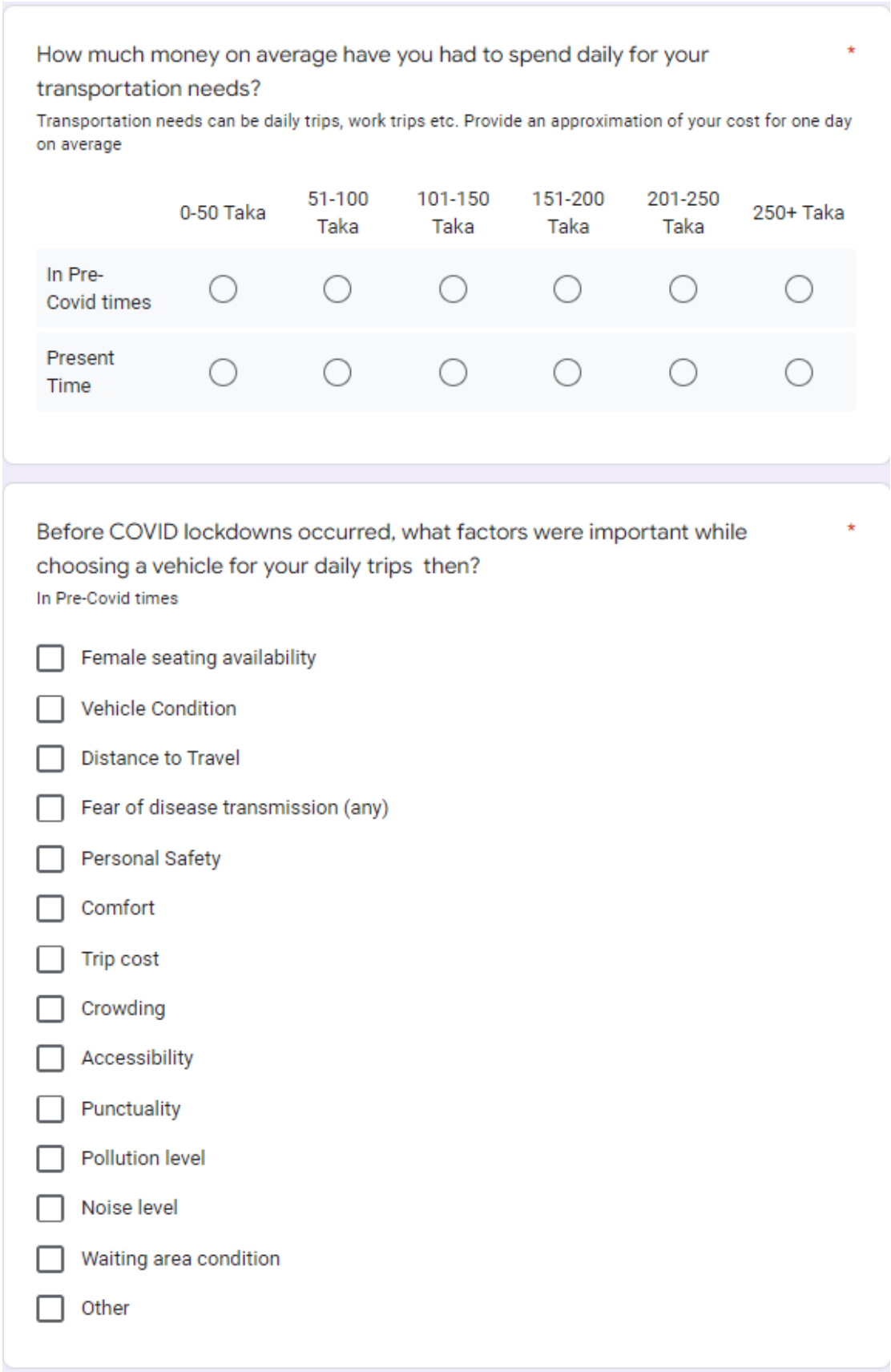


Figure A-10. Most Frequented Mode Section (continued) containing cost, Selection of LOS Factors in Pre-Covid

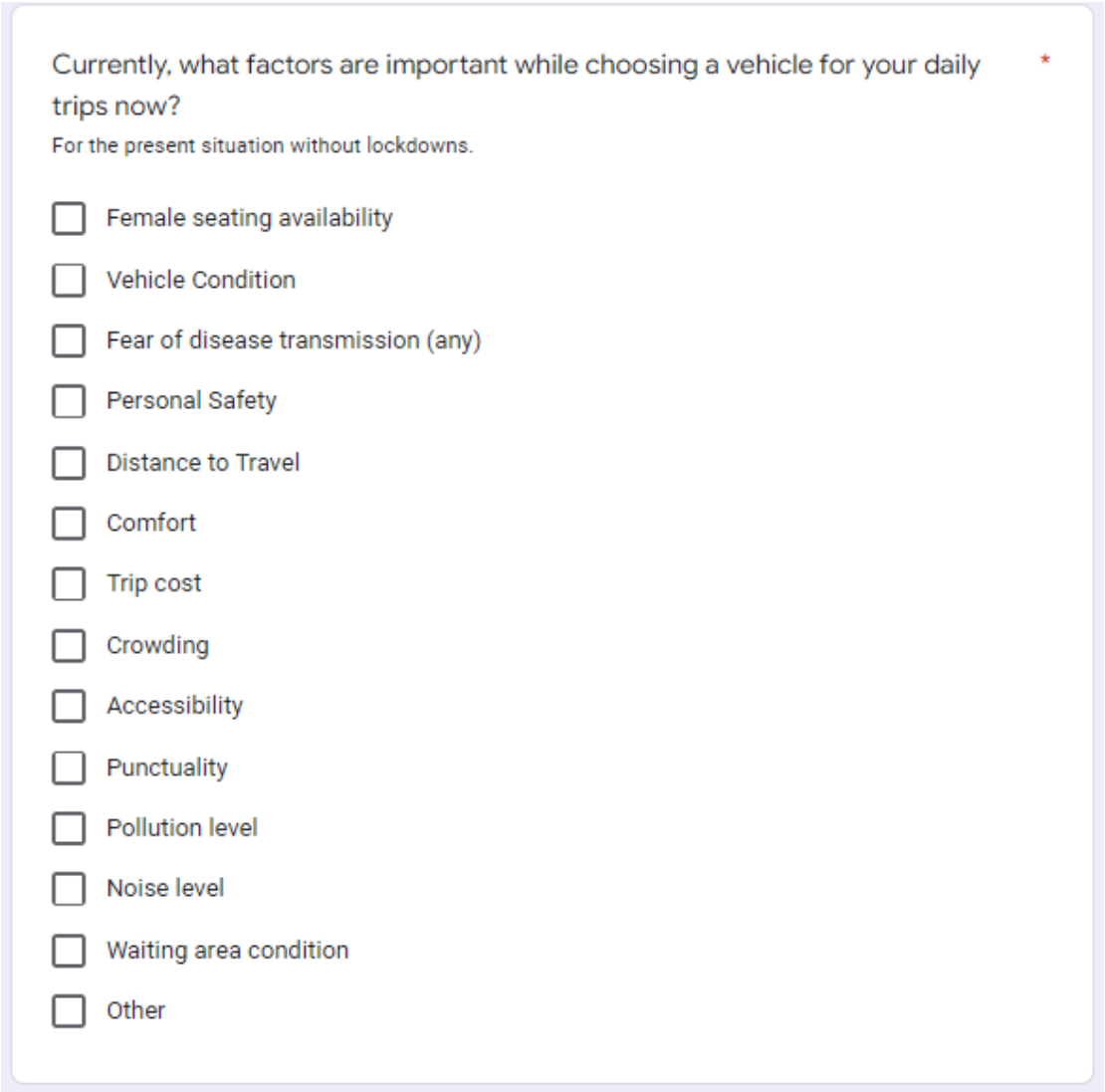


Figure A-11. Most Frequented Mode Section (end) containing selection of LOS factors in post-lockdown

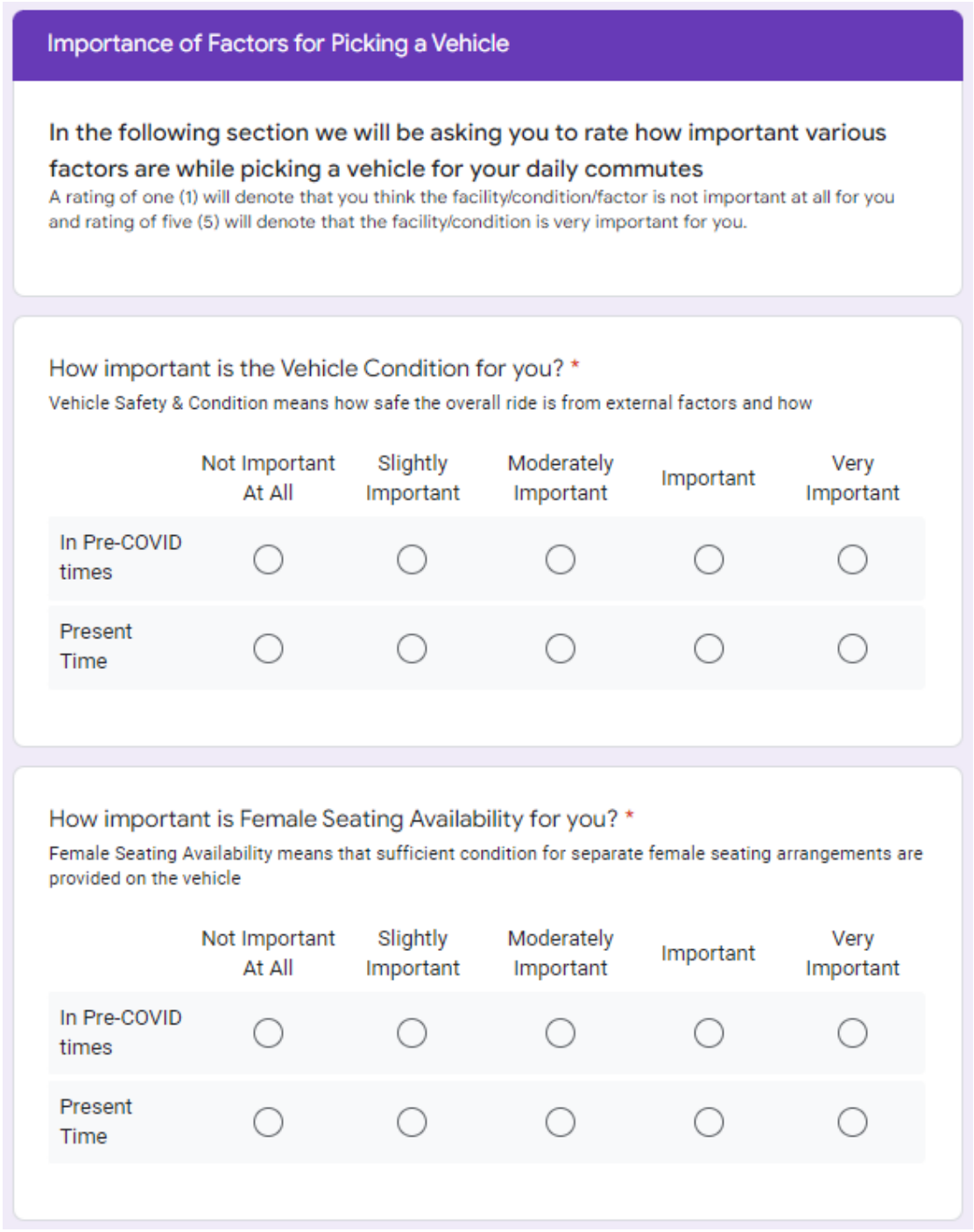


Figure A-12. Importance Imparted on Factors Section (start) containing Vehicle Condition and Female Seating Availability

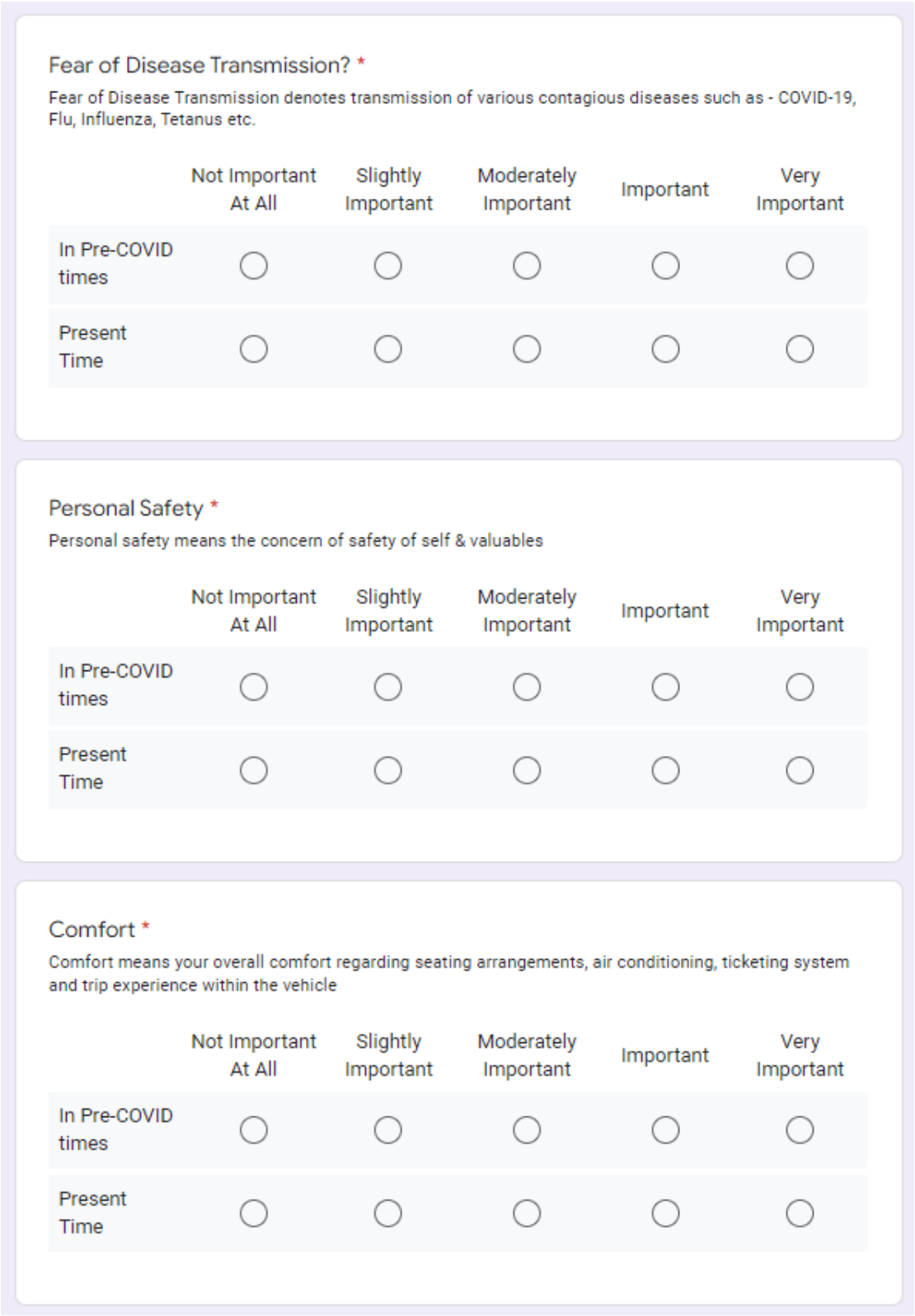


Figure A-13. Importance Imparted on Factors Section (continued) containing Fear of Disease Transmission, Safety and Comfort

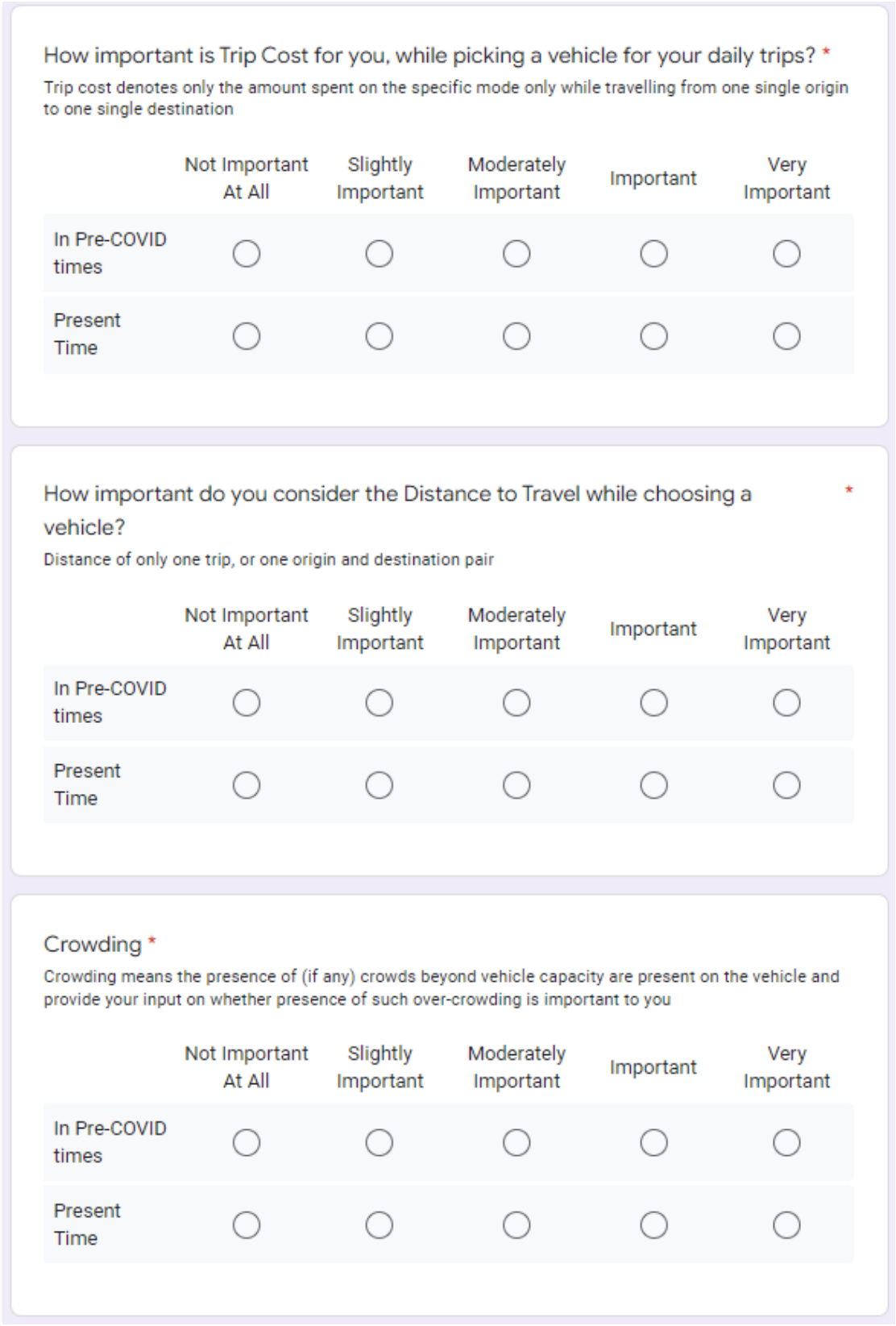


Figure A-14. Importance Imparted on Factors Section (continued) containing Trip Cost, Distance to Travel, Crowding

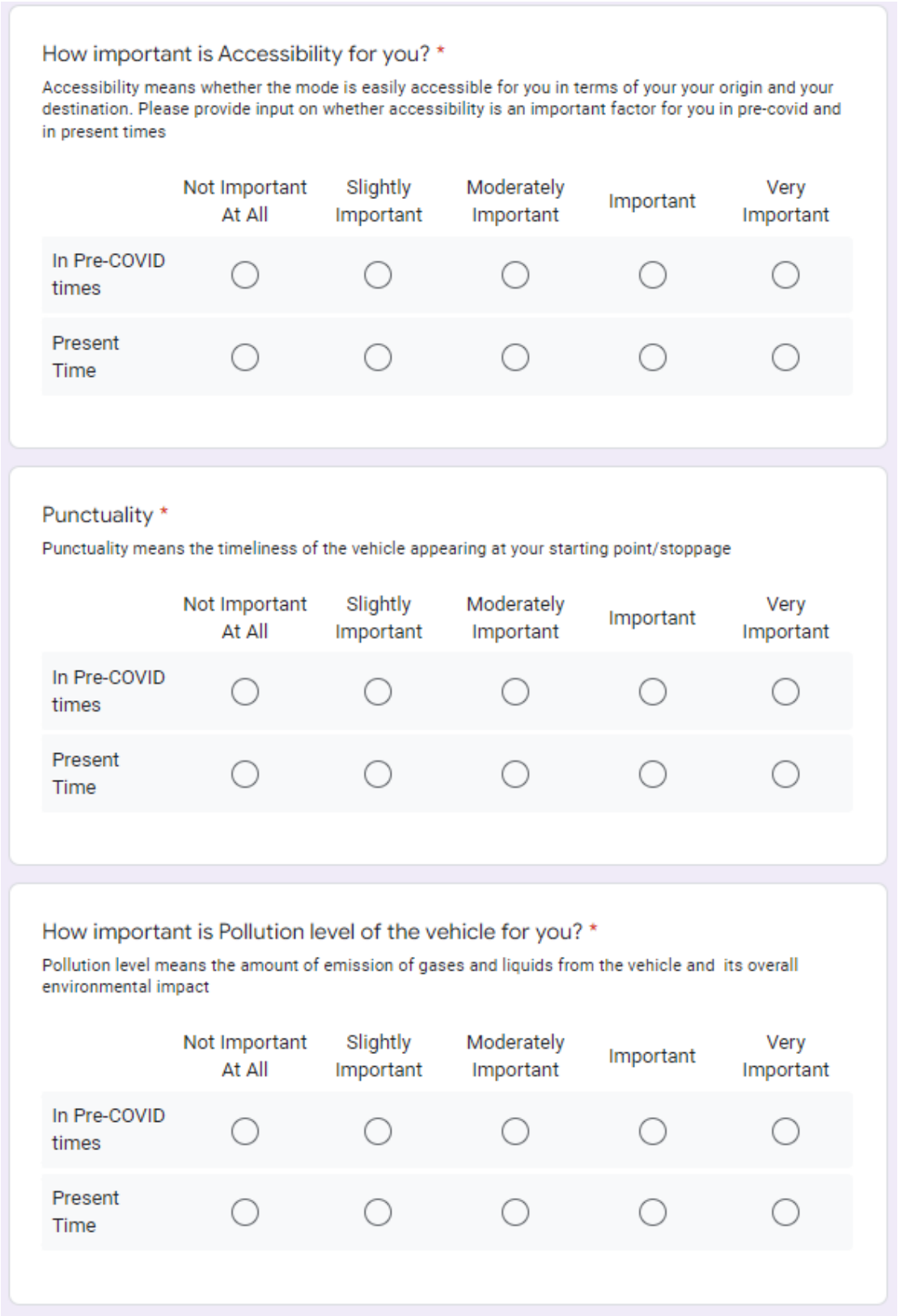


Figure A-15. Importance Imparted on Factors Section (continued) containing Accessibility, Punctuality and Pollution Level

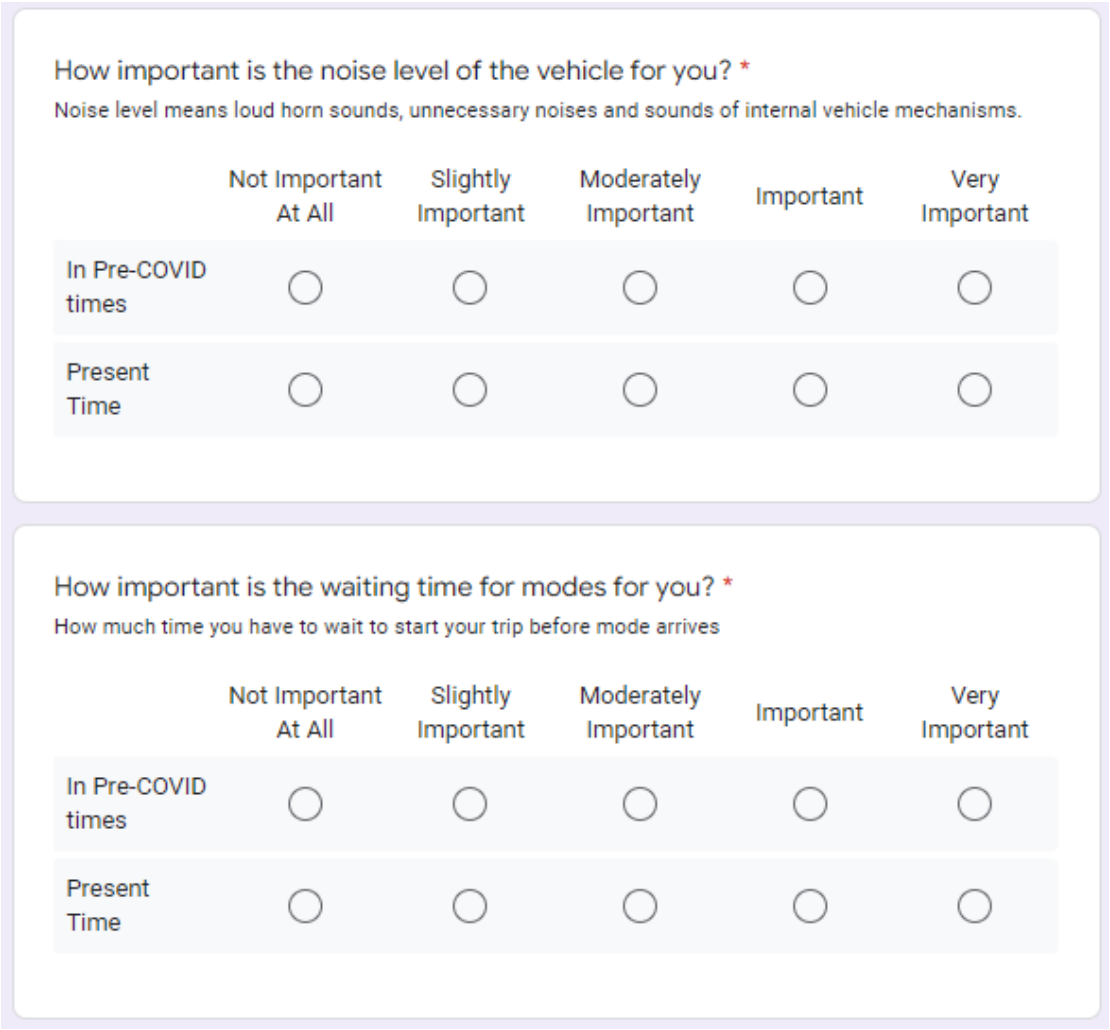


Figure A-16. Importance Imparted on Factors Section (end) containing Noise Level and Waiting time

Appendix B

Pre-Lockdown model estimated first. For that purpose, the following libraries are imported.

```
# Libraries Used in Code
import numpy as np
import pandas as pd
import pandas_profiling as pp
import math
import random as rnd
import os
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# preprocessing
import sklearn
from sklearn.preprocessing import LabelEncoder, StandardScaler,
MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

import warnings
warnings.filterwarnings("ignore")
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
pd.set_option('display.max_columns', None)
```

Firstly, the pre-lockdown data is imported and correlation among variables are checked using the following code snippet. The output heat map is shown in Figure B-1.

```
#Loading Attitude Data
X_attitude = pd.read_excel('DataNew.xlsx', sheet_name='Pre_Attitude')
#Loading Total Data
X = pd.read_excel('DataNew.xlsx', sheet_name='Pre')
X= pd.concat([X, X_attitude], axis=1).reindex(X.index)
#Checking for correlation between the values, if high correlation
exists then need to do dimensionality reduction
plt.figure(figsize=(20,10))
c= X.corr()
sns.heatmap(c)
```

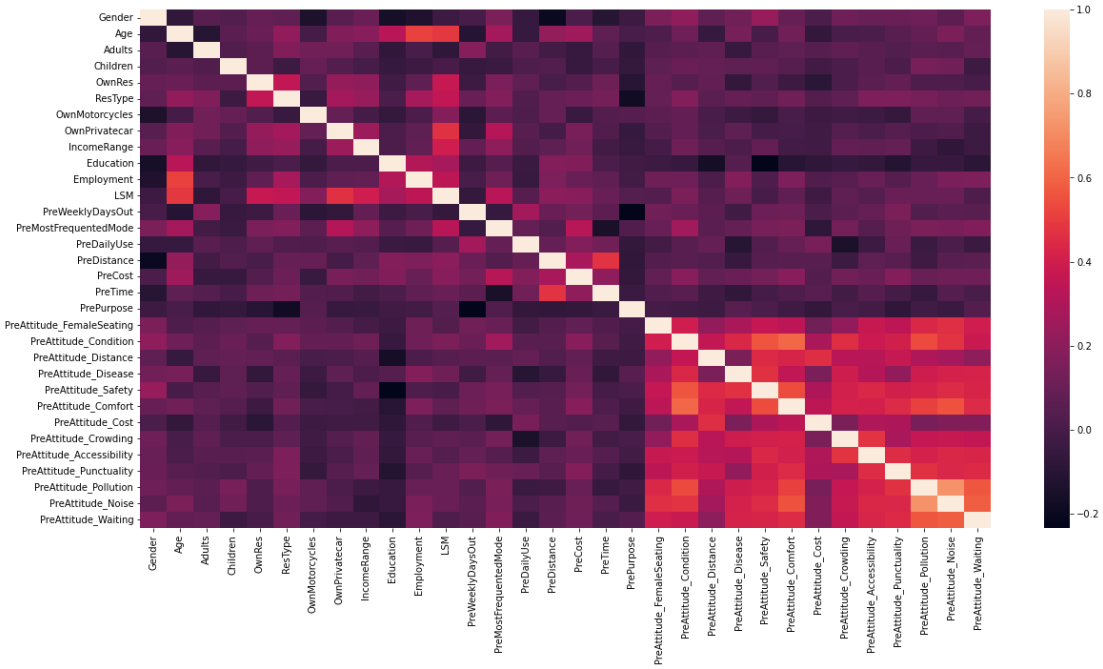


Figure B-1. Output of Variable Correlation Heatmap

As high correlation was present between attitude variables, they were to be reduced to latent factors using Exploratory Factor Analysis. However, suitability of EFA was checked using Kaiser-Meyer-Olkin Test and Bartlett's Test of Sphericity using the following snippet.

```
#Plot above shows high correlation, so we should do Dimensionality
Reduction
# Now, EFA is a method for DR, but to check whether our data supports
using EFA
# We need to check bartlett sphericitiy and KMO

#Check values based on EFA Interpretation


from factor_analyzer.factor_analyzer import
calculate_bartlett_sphericity
from factor_analyzer.factor_analyzer import calculate_kmo

chi_square_value,p_value=calculate_bartlett_sphericity(X_attitude)
print(chi_square_value, p_value)

#KMO
#Value should be 0.6<
kmo_all,kmo_model=calculate_kmo(X_attitude)
print(kmo_model)
```

The snippet's output is summarized in Table 5-2. Then, as the test results were satisfactory, Scree test was conducted to check change in Eigenvalue corresponding to number of latent factors, using the following code snippet which outputted figure B-2.

```
from factor_analyzer import FactorAnalyzer

fa = FactorAnalyzer(rotation = 'varimax',impute =
"drop",n_factors=X_attitude.shape[1])
fa.fit(X_attitude)
ev,_ = fa.get_eigenvalues()

#Using Scree Plot to check how many factors to use ----- EFA
Interpretation
plt.scatter(range(1,X_attitude.shape[1]+1),ev)
plt.plot(range(1,X_attitude.shape[1]+1),ev)
plt.title('Scree Plot for Pre-Lockdown Data')
plt.xlabel('Factors')
plt.ylabel('Eigen Value')
plt.grid()
```

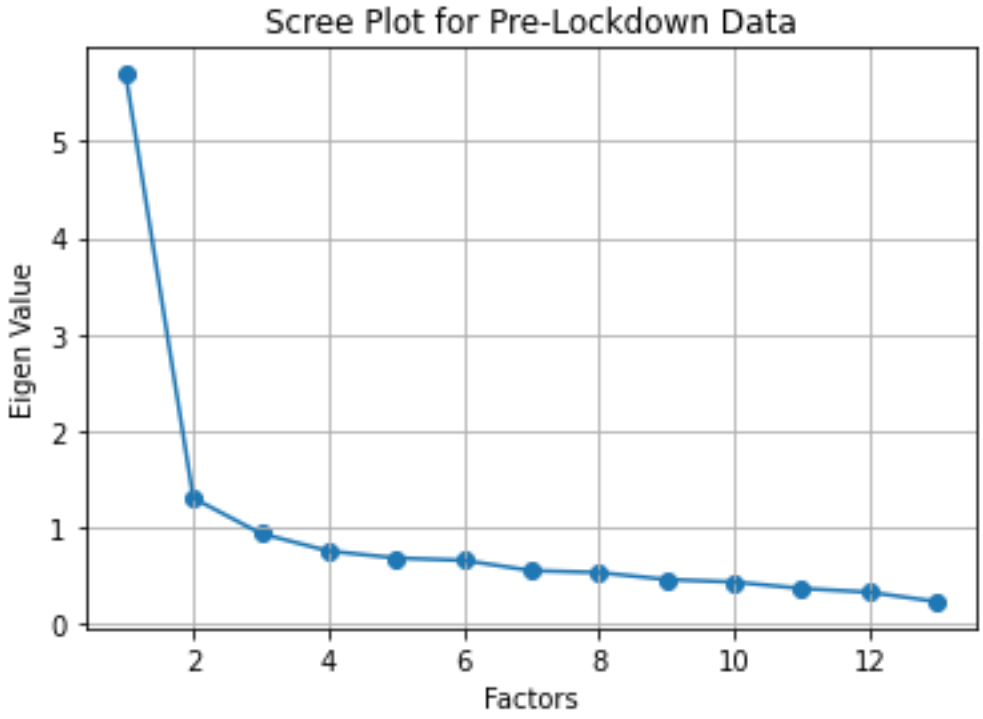


Figure B-2. Scree-Plot

The scree plot showed that using 3 factors would significantly account for the variance of the attitude data. Thus, 3 factors were used and the variables were reduced to the latent variables using the following code. The variables' loadings, communality and the factors' variance is also outputted.

```
fa = FactorAnalyzer(n_factors=3,rotation='varimax')
X_transformed = fa.fit_transform(X_attitude)

#prints out the loadings, variance and communalities ---- check EFA
Interpretation for explanation
print(pd.DataFrame(fa.loadings_,index=X_attitude.columns))
print(pd.DataFrame(fa.get_factor_variance(),index=['Variance','Propor
tional Var','Cumulative Var']))

print(pd.DataFrame(fa.get_communalities(),index=X_attitude.columns))
```

The following output was obtained from the code snippet above.

```
                                0         1         2
PreAttitude_FemaleSeating  0.482944  0.237682  0.148143
PreAttitude_Condition      0.371875  0.542849  0.336659
PreAttitude_Distance       0.150073  0.173454  0.688888
PreAttitude_Disease        0.285724  0.618239  0.030430
PreAttitude_Safety         0.302850  0.556525  0.399640
PreAttitude_Comfort        0.435046  0.409095  0.436423
PreAttitude_Cost           0.065793  0.105173  0.599119
PreAttitude_Crowding       0.247307  0.510325  0.240850
PreAttitude_Accessibility  0.402877  0.331950  0.349148
PreAttitude_Punctuality    0.495511  0.135123  0.427722
PreAttitude_Pollution      0.759111  0.282210  0.147390
PreAttitude_Noise          0.773046  0.301108  0.128904
PreAttitude_Waiting        0.618351  0.322919  0.122699
                         0         1         2
Variance          2.786207  1.915090  1.736153
Proportional Var  0.214324  0.147315  0.133550
Cumulative Var    0.214324  0.361638  0.495188
                                0
PreAttitude_FemaleSeating  0.311674
PreAttitude_Condition      0.546315
PreAttitude_Distance       0.527175
PreAttitude_Disease        0.464784
PreAttitude_Safety         0.561151
PreAttitude_Comfort        0.547089
PreAttitude_Cost           0.374333
PreAttitude_Crowding       0.379601
PreAttitude_Accessibility  0.394405
PreAttitude_Punctuality    0.446736
PreAttitude_Pollution      0.677617
PreAttitude_Noise          0.704882
PreAttitude_Waiting        0.501689
```

Cronbach's Alphas of the factors were tested to check whether EFA was a success using the following code snippet.

```
factor1 =
X_attitude[['PreAttitude_FemaleSeating','PreAttitude_Accessibility',
'PreAttitude_Punctuality', 'PreAttitude_Pollution',
'PreAttitude_Noise', 'PreAttitude_Waiting']]
factor2 = X_attitude[['PreAttitude_Condition', 'PreAttitude_Disease',
'PreAttitude_Safety','PreAttitude_Crowding']]
factor3 = X_attitude[['PreAttitude_Distance', 'PreAttitude_Comfort',
'PreAttitude_Cost']]


#Get cronbach alpha
import pingouin as pg
factor1_alpha = pg.cronbach_alpha(factor1)
factor2_alpha = pg.cronbach_alpha(factor2)
factor3_alpha = pg.cronbach_alpha(factor3)
print(factor1_alpha, factor2_alpha, factor3_alpha)
```

Which outputted the following values. The values were tested against baseline of 0.7.

```
(0.8365007716103853, array([0.806, 0.864])) (0.7664589851830943,
array([0.72 , 0.807])) (0.6757959191224083, array([0.606, 0.735]))
```

Then the main model was estimated and calibrated.

```
#Main Model
import statsmodels.api as sm

#Loading data
XX_train= pd.read_excel('DataNew.xlsx', sheet_name='Pre')

#Creating label variable
YY_train = XX_train[["PreMostFrequentedMode"]]
XX_train.drop("PreMostFrequentedMode", axis=1,inplace=True)



#Merging the input variables with the latent variables from EFA
XX_train = pd.concat([XX_train, X_transformed],
axis=1).reindex(XX_train.index)



#Creating model
#The
logit_model=sm.MNLogit(YY_train,sm.add_constant(XX_train))
logit_model

#Fitting model, using lbfgs method because some inputs are identical
and thus, we can not get hessian
#that is, our input matrix is not invertable, so using lbfgs instead
of newton


result=logit_model.fit(method='lbfgs',maxiter=10000)
stats1=result.summary()

print(stats1)
```

Which outputted the coefficients, their p-values, log-likelihood, r^2 tests etc.

```
                          MNLogit Regression Results
==============================================================================
Dep. Variable:     PreMostFrequentedMode   No. Observations:
295
Model:                          MNLogit   Df Residuals:
253
Method:                            MLE   Df Model:
40
Date:                 Sun, 08 May 2022   Pseudo R-squ.:
0.4682
Time:                         11:55:37   Log-Likelihood:
-171.57
converged:                        True   LL-Null:
-322.61
Covariance Type:            nonrobust   LLR p-value:
6.126e-14
=======================================================================
PreMostFrequentedMode=1       coef    std err          z      P>|z|
[0.025      0.975]
-----------------------------------------------------------------------
const                       0.3530      0.920      0.384      0.701
-1.451       2.157
Gender                      0.6041      0.459      1.317      0.188
-0.295       1.503
Age                         1.5302      0.560      2.734      0.006
0.433       2.627
Adults                      0.0183      0.169      0.108      0.914
-0.313       0.349
Children                   -0.2042      0.193     -1.060      0.289
-0.582       0.173
OwnRes                      0.1189      0.435      0.273      0.785
-0.733       0.971
ResType                     0.2716      0.183      1.484      0.138
-0.087       0.630
OwnMotorcycles              0.7475      0.245      3.047      0.002
0.267       1.228
OwnPrivatecar              -0.3591      0.351     -1.022      0.307
-1.048       0.329
IncomeRange                -0.1108      0.180     -0.614      0.539
-0.464       0.243
Education                  -0.1710      0.175     -0.979      0.328
-0.513       0.171
Employment                 -0.5307      0.329     -1.615      0.106
-1.175       0.114
PreWeeklyDaysOut           -0.1315      0.106     -1.242      0.214
-0.339       0.076
PreDailyUse                 0.2931      0.125      2.341      0.019
0.048       0.538
PreDistance                -0.3692      0.141     -2.611      0.009
-0.646      -0.092
PreCost                     0.2909      0.138      2.114      0.035
0.021       0.561
PreTime                    -0.7001      0.197     -3.556      0.000
-1.086      -0.314
```

PrePurpose	0.8494	0.375	2.266	0.023	
0.115	1.584				
Variable 1	-0.1407	0.219	-0.643	0.520	
-0.570	0.288				
Variable 2	0.9299	0.275	3.387	0.001	
0.392	1.468				
Variable 3	0.0730	0.229	0.319	0.749	
-0.375	0.521				

PreMostFrequentedMode=2	coef	std err	z	P>|z|	
[0.025	0.975]				
const	-1.1025	0.957	-1.153	0.249	
-2.977	0.772				
Gender	0.9025	0.454	1.988	0.047	
0.013	1.792				
Age	1.4692	0.524	2.802	0.005	
0.442	2.497				
Adults	-0.0878	0.169	-0.520	0.603	
-0.419	0.243				
Children	-0.3791	0.202	-1.877	0.061	
-0.775	0.017				
OwnRes	0.7547	0.414	1.821	0.069	
-0.058	1.567				
ResType	0.0305	0.177	0.172	0.864	
-0.317	0.378				
OwnMotorcycles	0.3409	0.253	1.348	0.178	
-0.155	0.837				
OwnPrivatecar	0.9496	0.269	3.525	0.000	
0.422	1.478				
IncomeRange	0.1814	0.178	1.020	0.308	
-0.167	0.530				
Education	-0.1693	0.182	-0.930	0.352	
-0.526	0.187				
Employment	-0.1443	0.298	-0.484	0.628	
-0.728	0.440				
PreWeeklyDaysOut	-0.1790	0.109	-1.649	0.099	
-0.392	0.034				
PreDailyUse	0.2516	0.123	2.049	0.040	
0.011	0.492				
PreDistance	0.0780	0.134	0.581	0.561	
-0.185	0.341				
PreCost	0.6080	0.145	4.195	0.000	
0.324	0.892				
PreTime	-0.7677	0.187	-4.095	0.000	
-1.135	-0.400				
PrePurpose	0.3667	0.450	0.815	0.415	
-0.515	1.249				
Variable 1	0.3905	0.228	1.717	0.086	
-0.055	0.836				
Variable 2	0.4510	0.267	1.691	0.091	
-0.072	0.974				
Variable 3	-0.1962	0.234	-0.839	0.401	
-0.654	0.262				

The odds Ratio and Confidence Interval of Odds Ratio were obtained by the following snippet.

```
params = result.params
conf = result.conf_int()
#conf['OR'] = params[]
conf.columns = ["Lower CI of OR", "Upper CI of OR"]
params.columns=["PreMostFrequentedMode=1","PreMostFrequentedMode=2"]

df=conf.T
df1=df.xs('1', level='PreMostFrequentedMode', axis=1).T
df2=df.xs('2', level='PreMostFrequentedMode', axis=1).T
df1=pd.concat([df1, params["PreMostFrequentedMode=1"]], axis=1)
df2=pd.concat([df2, params["PreMostFrequentedMode=2"]], axis=1)
df1.rename(columns = {'PreMostFrequentedMode=1':'Odds Ratio'},
inplace = True)
df2.rename(columns = {'PreMostFrequentedMode=2':'Odds Ratio'},
inplace = True)


df1=np.exp(df1)
df2=np.exp(df2)
print("PreMostFrequentedMode_1\n")
df1
print("PreMostFrequentedMode_2\n")
df2
```

Which outputted the following

```
PreMostFrequentedMode_1
```

Out[41]:

	Lower CI of OR	Upper CI of OR	Odds Ratio
const	0.234447	8.641132	1.423338
Gender	0.744834	4.494349	1.829630
Age	1.542006	13.837574	4.619266
Adults	0.731569	1.417817	1.018445
Children	0.558896	1.189277	0.815280
OwnRes	0.480240	2.641436	1.126287
ResType	0.916636	1.878139	1.312086
OwnMotorcycles	1.305556	3.415691	2.111723
OwnPrivatecar	0.350798	1.389973	0.698284
IncomeRange	0.628610	1.274685	0.895142
Education	0.598588	1.186823	0.842863
Employment	0.308859	1.120236	0.588214

	Lower CI of OR	Upper CI of OR	Odds Ratio
PreWeeklyDaysOut	0.712457	1.078982	0.876771
PreDailyUse	1.048857	1.713369	1.340552
PreDistance	0.523933	0.912012	0.691255
PreCost	1.021404	1.751878	1.337676
PreTime	0.337579	0.730333	0.496533
PrePurpose	1.121442	4.875636	2.338321
Variable 1	0.565804	1.333927	0.868758
Variable 2	1.479680	4.340629	2.534313
Variable 3	0.687269	1.683722	1.075718

PreMostFrequentedMode_2

Out[41]:

	Lower CI of OR	Upper CI of OR	Odds Ratio
const	0.050929	2.164920	0.332050
Gender	1.012828	6.003373	2.465843
Age	1.555268	12.143272	4.345808
Adults	0.657964	1.275151	0.915971
Children	0.460663	1.016942	0.684447
OwnRes	0.944013	4.791962	2.126893
ResType	0.728144	1.459681	1.030950
OwnMotorcycles	0.856633	2.308345	1.406202
OwnPrivatecar	1.524341	4.382559	2.584669
IncomeRange	0.845912	1.699281	1.198933
Education	0.590924	1.206154	0.844242
Employment	0.482744	1.552057	0.865590
PreWeeklyDaysOut	0.675845	1.034339	0.836094
PreDailyUse	1.010960	1.636079	1.286083
PreDistance	0.830839	1.406918	1.081167
PreCost	1.382562	2.440371	1.836836
PreTime	0.321360	0.670144	0.464066
PrePurpose	0.597346	3.485495	1.442930

	Lower CI of OR	Upper CI of OR	Odds Ratio
Variable 1	0.946130	2.308163	1.477776
Variable 2	0.930676	2.648037	1.569861
Variable 3	0.519905	1.299270	0.821886

Finally, accuracy of the model was tested.

```
#Checking Accuracy without dummies
from sklearn.metrics import accuracy_score

y_pred = result.predict(sm.add_constant(XX_train))


maxValueIndex = y_pred.idxmax(axis = 1)
score =accuracy_score(YY_train,maxValueIndex)
#print(y_pred)
#print(maxValueIndex)
score


Output: 0.6949152542372882
```

Similarly, the analysis for post-Lockdown analysis was done and are exempt from reiteration here.

Finally, the interaction of the time-period with the different models were analyzed by the following code. The methodology of the process are explained in Chapter Three.

```
#Combined Interaction data to compare pre and post
comb1 = pd.read_excel('DataNew.xlsx', sheet_name='Comb1')
pred = comb1[["MostFrequentedMode"]]
comb1.drop("MostFrequentedMode", axis=1,inplace=True)
logit_model=sm.MNLogit(pred,sm.add_constant(comb1))
logit_model

result=logit_model.fit(method='lbfgs',maxiter=10000)
stats1=result.summary()
stats2=result.summary2()
print(stats1)
```

The following output was obtained and tabulated.

```
<statsmodels.discrete.discrete_model.MNLogit at 0x1f69c40aa60>
                          MNLogit Regression Results
==============================================================================
Dep. Variable:     MostFrequentedMode   No. Observations:
590
Model:                        MNLogit   Df Residuals:
506
Method:                           MLE   Df Model:
82
Date:                Sat, 07 May 2022   Pseudo R-squ.:
0.3654
Time:                        20:01:00   Log-Likelihood:
-191.11
converged:                       True   LL-Null:
-411.33
Covariance Type:            nonrobust   LLR p-value:
4.749e-33
==============================================================================
 MostFrequentedMode=1       coef    std err          z      P>|z|
[0.025      0.975]
------------------------------------------------------------------------------
const                     0.3592      0.920      0.390      0.696
-1.445       2.163
Gender                    0.6025      0.459      1.314      0.189
-0.296       1.501
Age                       1.5317      0.560      2.736      0.006
0.434       2.629
Adults                    0.0179      0.169      0.106      0.916
-0.313       0.349
Children                 -0.2042      0.193     -1.060      0.289
-0.582       0.173
OwnRes                    0.1188      0.435      0.273      0.785
-0.734       0.971
ResType                   0.2719      0.183      1.486      0.137
-0.087       0.631
OwnMotorcycles            0.7476      0.245      3.047      0.002
0.267       1.229
OwnPrivatecar            -0.3600      0.351     -1.025      0.306
-1.048       0.329
IncomeRange              -0.1113      0.180     -0.617      0.537
-0.465       0.242
Education                -0.1717      0.175     -0.983      0.325
-0.514       0.171
Employment               -0.5303      0.329     -1.613      0.107
-1.175       0.114
PreWeeklyDaysOut         -0.1319      0.106     -1.245      0.213
-0.339       0.076
PreDailyUse               0.2931      0.125      2.341      0.019
0.048       0.539
PreDistance              -0.3695      0.141     -2.613      0.009
-0.647      -0.092
PreCost                   0.2910      0.138      2.114      0.034
0.021       0.561
PreTime                  -0.7004      0.197     -3.557      0.000
-1.086      -0.314
```

```
PrePurpose                 0.8494      0.375      2.265      0.023
0.114       1.584
Variable 1                -0.1413      0.219     -0.646      0.518
-0.570       0.288
Variable 2                 0.9308      0.275      3.390      0.001
0.393       1.469
Variable 3                 0.0723      0.229      0.316      0.752
-0.376       0.520
Time                       1.4157      1.373      1.031      0.302
-1.275       4.106
Gender:Time               -0.4171      0.672     -0.621      0.535
-1.734       0.900
Age:Time                  -1.4099      0.796     -1.771      0.077
-2.971       0.151
Adults:Time               -0.0384      0.247     -0.156      0.876
-0.522       0.445
Children:Time             -0.0101      0.275     -0.037      0.971
-0.549       0.529
OwnRes:Time                0.0705      0.622      0.113      0.910
-1.148       1.289
ResType:Time              -0.3853      0.259     -1.488      0.137
-0.893       0.122
OwnMotorcycles:Time       -0.2160      0.369     -0.585      0.559
-0.940       0.508
OwnPrivatecar:Time        -0.2847      0.506     -0.563      0.574
-1.276       0.707
IncomeRange:Time           0.5505      0.273      2.020      0.043
0.016       1.085
Education:Time            -0.0664      0.253     -0.262      0.793
-0.563       0.430
Employment:Time            0.8114      0.498      1.628      0.103
-0.165       1.788
PreWeeklyDaysOut:Time     -0.0694      0.145     -0.479      0.632
-0.353       0.215
PreDailyUse:Time          -0.2305      0.181     -1.272      0.203
-0.586       0.125
PreDistance:Time           0.3938      0.188      2.095      0.036
0.025       0.762
PreCost:Time              -0.1603      0.187     -0.859      0.390
-0.526       0.205
PreTime:Time               0.0737      0.249      0.296      0.767
-0.414       0.562
PrePurpose:Time           -0.3948      0.514     -0.768      0.442
-1.402       0.612
Variable 1:Time            0.1882      0.308      0.611      0.541
-0.416       0.792
Variable 2:Time           -0.5303      0.360     -1.473      0.141
-1.236       0.175
Variable 3:Time           -0.2072      0.343     -0.604      0.546
-0.879       0.465
------------------------------------------------------------------------------
 MostFrequentedMode=2       coef    std err          z      P>|z|
[0.025      0.975]
------------------------------------------------------------------------------
const                     -1.0943      0.957     -1.144      0.253
-2.969       0.781
Gender                     0.9007      0.454      1.984      0.047
0.011       1.790
```

Age	1.4707	0.524	2.804	0.005	
0.443	2.498				
Adults	-0.0884	0.169	-0.524	0.601	
-0.419	0.242				
Children	-0.3792	0.202	-1.877	0.061	
-0.775	0.017				
OwnRes	0.7547	0.414	1.821	0.069	
-0.058	1.567				
ResType	0.0304	0.177	0.171	0.864	
-0.317	0.378				
OwnMotorcycles	0.3408	0.253	1.347	0.178	
-0.155	0.836				
OwnPrivatecar	0.9493	0.269	3.524	0.000	
0.421	1.477				
IncomeRange	0.1811	0.178	1.018	0.309	
-0.168	0.530				
Education	-0.1704	0.182	-0.936	0.349	
-0.527	0.186				
Employment	-0.1437	0.298	-0.482	0.630	
-0.728	0.440				
PreWeeklyDaysOut	-0.1793	0.109	-1.652	0.099	
-0.392	0.033				
PreDailyUse	0.2516	0.123	2.049	0.040	
0.011	0.492				
PreDistance	0.0778	0.134	0.579	0.562	
-0.186	0.341				
PreCost	0.6080	0.145	4.194	0.000	
0.324	0.892				
PreTime	-0.7679	0.187	-4.096	0.000	
-1.135	-0.400				
PrePurpose	0.3669	0.450	0.815	0.415	
-0.515	1.249				
Variable 1	0.3900	0.228	1.714	0.086	
-0.056	0.836				
Variable 2	0.4512	0.267	1.691	0.091	
-0.072	0.974				
Variable 3	-0.1964	0.234	-0.841	0.401	
-0.654	0.262				
Time	1.0413	1.421	0.733	0.464	
-1.744	3.826				
Gender:Time	-0.2534	0.661	-0.383	0.701	
-1.549	1.042				
Age:Time	-1.0915	0.750	-1.455	0.146	
-2.562	0.379				
Adults:Time	-0.0365	0.249	-0.146	0.884	
-0.525	0.452				
Children:Time	0.1036	0.288	0.360	0.719	
-0.460	0.668				
OwnRes:Time	0.0796	0.594	0.134	0.893	
-1.084	1.243				
ResType:Time	-0.2458	0.253	-0.971	0.331	
-0.742	0.250				
OwnMotorcycles:Time	0.2699	0.376	0.719	0.472	
-0.466	1.006				
OwnPrivatecar:Time	-0.4159	0.390	-1.068	0.286	
-1.180	0.348				
IncomeRange:Time	0.4033	0.266	1.514	0.130	
-0.119	0.925				
Education:Time	-0.0416	0.260	-0.160	0.873	
-0.551	0.468				

```
Employment:Time            0.8219      0.468      1.757      0.079
-0.095       1.739
PreWeeklyDaysOut:Time      0.0381      0.149      0.256      0.798
-0.254       0.330
PreDailyUse:Time          -0.2100      0.177     -1.187      0.235
-0.557       0.137
PreDistance:Time          -0.0125      0.180     -0.070      0.944
-0.366       0.340
PreCost:Time              -0.2735      0.190     -1.442      0.149
-0.645       0.098
PreTime:Time               0.5640      0.236      2.385      0.017
0.101       1.027
PrePurpose:Time           -0.2119      0.588     -0.360      0.719
-1.365       0.941
Variable 1:Time           -0.3371      0.321     -1.051      0.293
-0.965       0.291
Variable 2:Time            0.0219      0.356      0.062      0.951
-0.675       0.719
Variable 3:Time           -0.3226      0.349     -0.924      0.356
-1.007       0.362
================================================================================
====================
```

Appendix C

Appendix C-1. List of the variables used in the Exploratory Factor Analysis (EFA) with the particular encoding of their labels

Descriptors	Variable Name	Period Denoted	Value Labels
Availability of Female Seating Arrangements	PreAttitude_FemaleSeating	Before Lockdowns	Not Important at all = 0 Somewhat Important =1 Moderately Important = 2 Important = 3 Very Important =4
	PostAttitude_FemaleSeating	After Lockdown Repealing	
Condition of Vehicle and Seating Facilities	PreAttitude_Condition	Before Lockdowns	
	PostAttitude_Condition	After Lockdown Repealing	
Overall Vehicle and Personal Safety	PreAttitude_Safety	Before Lockdowns	
	PostAttitude_Safety	After Lockdown Repealing	
Accessibility	PreAttitude_Accessibility	Before Lockdowns	
	PostAttitude_Accessibility	After Lockdown Repealing	
Distance of Most Frequented Trip	PreAttitude_Distance	Before Lockdowns	
	PostAttitude_Distance	After Lockdown Repealing	
Fear of Disease Transmissibility	PreAttitude_Disease	Before Lockdowns	
	PostAttitude_Disease	After Lockdown Repealing	
Comfort of Vehicle and Trip	PreAttitude_Comfort	Before Lockdowns	
	PostAttitude_Comfort	After Lockdown Repealing	
	PreAttitude_Cost	Before Lockdowns	

Cost of Mode in Most Frequented Trip	PostAttitude_Cost	After Lockdown Repealing	

Appendix C-1. ***(continued)***

Crowding in Most Frequented Mode	PreAttitude_Crowding	Before Lockdowns	Not Important at all = 0 Somewhat Important =1 Moderately Important = 2 Important = 3 Very Important =4
	PostAttitude_Crowding	After Lockdown Repealing	
Punctuality of Driver and Mode Frequency	PreAttitude_Punctuality	Before Lockdowns	
	PostAttitude_Punctuality	After Lockdown Repealing	
Air and Other Pollution Expected from Mode and on Trip	PreAttitude_Pollution	Before Lockdowns	
	PostAttitude_Pollution	After Lockdown Repealing	
Noise from Mode and External Source in Trip	PreAttitude_Noise	Before Lockdowns	
	PostAttitude_Noise	After Lockdown Repealing	
Waiting Time for Mode	PreAttitude_Waiting	Before Lockdowns	
	PostAttitude_Waiting	After Lockdown Repealing	

Appendix D

Appendix D-1. List of the variables used in mode choice models with the particular encoding of their labels

Descriptors	Variable Name	Period Denoted	Value Labels
Socio-Demographic Variables			
Gender	Gender	-	Male = 0 Famale = 1
Age Group	Age	-	16-25=0 26-35=1 36-45=2 46-55=3 56-65=4 Above 65=5
Number of Adults in HH	Adults	-	0 = 0 1 = 1 2 = 2 3 = 3 4 = 4 More than 4 = 5
Number of Adults in HH	Children	-	0 = 0 1 = 1 2 = 2 3 = 3 4 = 4 More than 4 = 5
Ownership of Residence	OwnRes	-	No = 0 Yes = 1
Type of Residence	ResType	-	Hostel, Mess, Dormitory, Other = 0 Office Quarter = 1 Residential Building = 2 Commercial Building = 3 High Rise Apartment = 4

Number of Motorcycles Owned By HH	OwnMotorcycles	-	0 = 0 1 = 1 2 = 2 More than 2 = 3
Number of Private Cars Owned By HH	OwnPrivatecar	-	0 = 0 1 = 1 2 = 2 More than 2 = 3
Income Range of HH	Income Range	-	21,000-30,000 = 0 31,000-40,000 = 1 41,000-50,000 = 2 More than 50,000 = 3
Highest Level of Education of Respondent	Education	-	Secondary School Certificate (SSC) = 0 Higher Secondary Certificate (HSC) = 1 College degree, Diploma and Undergraduate = 2 Postgraduate and Ph.D. = 3
Employment Status of Respondent	Employment	-	Student = 0 Unemployed = 1 Self-Employed = 2 Employed = 3
	Trip Characteristics		
Number of Days Mode Used in a Week	PreWeeklyDaysOut	Before Lockdowns	0 = 0 1 = 1 2 = 2 3 = 3 4 = 4 5 = 5 Almost Every day = 6
	PostWeeklyDaysOut	After Lockdown Repealing	
Mode Used in Most Frequented Trip	PreMostFrequentedMode	Before Lockdowns	Public Bus, Leguna = Public Transport (PT) = 0 Private Car, Ride-Sharing, Motorcycle, CNG = Private Vehicle = 1
	PostMostFrequentedMode	After Lockdown Repealing	

			Rickshaw, Cycle, Walk = Non-Motorized Vehicle = 3
Number of Times Most Frequented Trip Made in A Day	PreDailyUse	Before Lockdowns	0 = 0 1 = 1 2 = 2 3 = 3 4 = 4 5 = 5 More than 6 = 7
	PostDailyUse	After Lockdown Repealing	
Typical Distance Travelled in Most Frequented Trip	PreDistance	Before Lockdowns	Less than 2 Kilometers = 0 2 Km - 4 Km = 1 4 Km - 6 Km = 2 6 km - 8 Km = 3 8-10 Km = 4 More than 10 Km = 5
	PostDistance	After Lockdown Repealing	
Typical Cost of Most Frequented Trip	PreCost	Before Lockdowns	0-50 Taka = 0 51-100 Taka = 1 101-150 Taka = 2 151-200 Taka = 3 201-250 Taka = 4 More than 250 Taka = 5
	PostCost	After Lockdown Repealing	
Typical Travel Time of Most Frequented Trip	PreTime	Before Lockdowns	Less than 30 mins = 0 30 – 1 hour = 1 1 – 1.5 = 2 1.5 – 2 = 3 More than 2 = 4
	PostTime	After Lockdown Repealing	
Purpose of Most Frequented Trip	PrePurpose	Before Lockdowns	Education, Work, Children Care = 0 Social-Visit, Shopping and Recreation = 1 Health Care and Others = 2
	PostPurpose	After Lockdown Repealing	
Reduced Importance Imparted on Various Levels of Service (LOS) and Trip Attributes			
External Attributes of Mode	PreVariable1	Before Lockdowns	Numerical
	PostVariable1	After Lockdown Repealing	

Safety and Distancing in Mode	PreVariable2	Before Lockdowns	Numerical
	PostVariable2	After Lockdown Repealing	
Trip Related Attributes	PreVariable3	Before Lockdowns	Numerical
	PostVariable3	After Lockdown Repealing	
Comparison Related	TimePeriod	-	Before Lockdown = 0 After Lockdown =1

Appendix E

Table E. 1: Mode of transportation used by travelers according to their gender before lockdown

			Mode							
			Public Bus	Private Car	Motorcycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk
Gender	Male	Count	85	38	15	39	18	18	6	7
		% within Gender	37.61	16.81	6.64	17.26	7.96	7.96	2.65	3.10
		% within Mode	85.86	61.29	100	65	100	66.67	100	70
	Female	Count	14	24	0	21	0	9	0	3
		% within Gender	19.72	33.80	0	29.58	0	12.68	0	4.23
		% within Mode	14.14	38.71	0	35	0	33.33	0	30

Table E. 2: Mode of transportation used by travelers according to their gender in present situation

			Mode							
			Public Bus	Private Car	Motorcycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk
Gender	Male	Count	49	48	15	52	19	19	11	4
		% within Gender	22.58	22.12	6.91	23.96	8.76	8.76	5.07	1.84
		% within Mode	81.67	63.16	100	74.29	100	67.86	91.67	50
	Female	Count	11	28	0	18	0	9	1	4
		% within Gender	15.49	39.44	0	25.35	0	12.68	1.41	5.63
		% within Mode	18.33	36.84	0	25.71	0	32.14	8.33	50

Table E. 3: Mode of transportation used by travelers according to their age before lockdown

			Mode							
			Public Bus	Private Car	Motorcycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk
Age Group	16-25	Count	89	40	11	51	15	19	1	8
		% within Age	38.03	17.09	4.70	21.79	6.41	8.12	0.43	3.42
		% within Mode	89.90	64.52	73.33	85	83.33	70.37	16.67	80
		Count	10	13	3	9	3	8	5	0

	26-35	% within Age	19.61	25.49	5.88	17.65	5.88	15.69	9.80	0
		% within Mode	10.10	20.97	21.42	15	16.67	29.63	83.33	0
	36-45	Count	0	6	1	0	0	0	0	1
		% within Age	0	75	12.50	0	0	0	0	12.50
		% within Mode	0	9.68	7.14	0	0	0	0	10
	46-55	Count	0	1	0	0	0	0	0	1
		% within Age	0	50	0	0	0	0	0	50
		% within Mode	0	1.61	0	0	0	0	0	10
	56-65	Count	0	2	0	0	0	0	0	0
		% within Age	0	100	0	0	0	0	0	0
		% within Mode	0	3.23	0	0	0	0	0	0
	Above 65	Count	0	0	0	0	0	0	0	0
		% within Age	0	0	0	0	0	0	0	0
		% within Mode	0	0	0	0	0	0	0	0

Mode of transportation used by travelers according to their age group in present situation

			Mode							
			Public Bus	Private Car	Motorcycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk
Age Group	16-25	Count	51	49	12	64	16	22	6	14
		% within Age	21.79	20.94	5.13	27.35	6.84	9.40	2.56	5.98
		% within Mode	85	64.47	80	91.43	84.21	78.57	50	82.35
	26-35	Count	9	17	3	6	3	6	6	1
		% within Age	17.65	33.33	5.88	11.76	5.88	11.76	11.76	1.96
		% within Mode	15	22.37	20	8.57	15.79	21.43	50	5.88
	36-45	Count	0	7	0	0	0	0	0	1
		% within Age	0	87.50	0	0	0	0	0	12.50
		% within Mode	0	9.21	0	0	0	0	0	5.88
	46-55	Count	0	1	0	0	0	0	0	1
		% within Age	0	50	0	0	0	0	0	50
		% within Mode	0	1.32	0	0	0	0	0	5.88
		Count	0	2	0	0	0	0	0	0

	56-65	% within Age	0	100	0	0	0	0	0	0
		% within Mode	0	2.63	0	0	0	0	0	0
	Above 65	Count	0	0	0	0	0	0	0	0
		% within Age	0	0	0	0	0	0	0	0
		% within Mode	0	0	0	0	0	0	0	0

Table E. 4: Mode of transportation used by travelers according to their household income before lockdown

			Mode							
			Public Bus	Private Car	Motor cycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk
Income Range		Count	7	0	1	2	0	2	0	0
	Less than 5000	% within Income range	58.33	0	8.33	16.67	0	16.67	0	0
		% within Mode	6.60	0	4.76	3.45	0	6.45	0	0
		Count	4	0	1	4	2	1	0	0
	5000-10000	% within Income range	33.33	0	8.33	33.33	16.67	8.33	0	0
		% within Mode	3.77	0	4.76	6.90	8.33	3.23	0	0
		Count	11	0	2	5	3	0	0	2
	11000-20000	% within Income range	47.83	0	8.70	21.74	13.04	0	0	8.70
		% within Mode	10.38	0	9.52	8.62	12.50	0	0	13.33
		Count	0	0	0	0	0	0	0	0
	21000-30000	% within Income range	0	0	0	0	0	0	0	0
		% within Mode	0	0	0	0	0	0	0	0
		Count	8	1	0	4	3	1	0	2
	31000-40000	% within Income range	42.11	5.26	0	21.05	15.79	5.26	0	10.53
		% within Mode	7.55	1.69	0	6.90	12.50	3.23	0	13.33
		Count	6	6	6	6	6	6	6	6
	41000-50000	% within Income range	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50
		% within Mode	5.66	10.17	28.57	10.34	25	19.35	50	40
		Count	41	34	7	24	4	12	5	1
	More than 50000	% within Income range	32.03	26.56	5.47	18.75	3.13	9.38	3.91	0.78
		% within Mode	38.68	57.63	33.33	41.38	16.67	38.71	41.67	6.67
		Count	29	18	4	13	6	9	1	4

	Prefer not to say	% within Income range	34.52	21.43	4.76	15.48	7.14	10.71	1.19	4.76
		% within Mode	27.36	30.51	19.05	22.41	25	29.03	8.33	26.67

Table E. 5: Mode of transportation used by travelers according to their household income in present situation

			Mode							
			Public Bus	Private Car	Motor cycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk
Income Range	Less than 5000	Count	5	2	1	1	1	2	0	0
		% within Income range	41.67	16.67	8.33	8.33	8.33	16.67	0	0
		% within Mode	5.21	5.26	7.69	1.54	5.26	7.69	0	0
	5000-10000	Count	2	0	1	4	3	1	0	1
		% within Income range	16.67	0	8.33	33.33	25	8.33	0	8.33
		% within Mode	2.08	0	7.69	6.15	15.79	3.85	0	6.25
	11000-20000	Count	10	1	2	5	3	0	0	2
		% within Income range	43.48	4.35	8.70	21.74	13.04	0	0	8.70
		% within Mode	10.42	2.63	15.38	7.69	15.79	0	0	12.50
	21000-30000	Count	0	0	0	0	0	0	0	0
		% within Income range	0	0	0	0	0	0	0	0
		% within Mode	0	0	0	0	0	0	0	0
	31000-40000	Count	3	2	0	7	3	2	0	2
		% within Income range	15.79	10.53	0	36.84	15.79	10.53	0	10.53
		% within Mode	3.13	5.26	0	10.77	15.79	7.69	0	12.50
	41000-50000	Count	1	1	1	1	1	1	1	1
		% within Income range	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50
		% within Mode	1.04	2.63	7.69	1.54	5.26	3.85	7.69	6.25
	More than 50000	Count	50	14	5	31	3	10	9	6
		% within Income range	39.06	10.94	3.91	24.22	2.34	7.81	7.03	4.69
		% within Mode	52.08	36.84	38.46	47.69	15.79	38.46	69.23	37.50
	Prefer not to say	Count	25	18	3	16	5	10	3	4
		% within Income range	29.76	21.43	3.57	19.05	5.95	11.90	3.57	4.76
		% within Mode	26.04	47.37	23.08	24.62	26.32	38.46	23.08	25

Table E. 6: Mode of transportation used by travelers according to education in pre covid situation

			Mode							
			Public Bus	Private Car	Motor cycle	Rick shaw	Cycle	Ride sharing apps	CNG	Walk
Education	SSC	Count	3	4	1	4	0	1	0	1
		% within Age	21.43	28.57	7.14	28.57	0	7.14	0	7.14
		% within Education	3.06	6.45	6.67	6.67	0	3.70	0	10
	HSC	Count	28	15	4	23	5	9	0	2
		% within Age	32.56	17.44	4.65	26.74	5.81	10.47	0	2.33
		% within Education	28.57	24.19	26.67	38.33	29.41	33.33	0	20
	UNNDERGRADUATE	Count	63	29	8	30	11	14	4	6
		% within Age	38.18	17.58	4.85	18.18	6.67	8.48	2.42	3.64
		% within Education	64.29	46.77	53.33	50	64.71	51.85	66.67	60
	POSTGRADUATE	Count	4	13	2	3	1	3	2	0
		% within Age	14.29	46.43	7.14	10.71	3.57	10.71	7.14	0
		% within Education	4.08	20.97	13.33	5	5.88	11.11	33.33	0
	DIPLOMA	Count	0	1	0	0	0	0	0	1
		% within Age	0	50	0	0	0	0	0	50
		% within Education	0	1.61	0	0	0	0	0	10

Table E. 7: Mode of transportation used by travelers according to their education in present situation

			Mode							
			Public Bus	Private Car	Motor cycle	Rick shaw	Cycle	Ride sharing apps	CNG	Walk
Education	SSC	Count	3	3	1	3	0	2	1	1
		% within Age	21.43	21.43	7.14	21.43	0	14.29	7.14	7.14
		% within Education	5	3.95	6.67	4.35	0	7.14	8.33	5.88
	HSC	Count	14	18	5	26	6	9	2	6
		% within Age	16.28	20.93	5.81	30.23	6.98	10.47	2.33	6.98
		% within Education	23.33	23.68	33.33	37.68	33.33	32.14	16.67	35.29
	UNDERGRADUATE	Count	41	41	8	34	11	15	6	9
		% within Age	24.85	24.85	4.85	20.61	6.67	9.09	3.64	5.45

		% within Education	68.33	53.95	53.33	49.28	61.11	53.57	50	52.94
	POSTGRADUATE	Count	2	13	1	6	1	2	3	0
		% within Age	7.14	46.43	3.57	21.43	3.57	7.14	10.71	0
		% within Education	3.33	17.11	6.67	8.70	5.56	7.14	25	0
	DIPLOMA	Count	0	1	0	0	0	0	0	1
		% within Age	0	50	0	0	0	0	0	50
		% within Education	0	1.32	0	0	0	0	0	5.88

Table E. 8: Mode of transportation used by travelers according to their occupation before lockdown

			Mode							
			Public Bus	Private Car	Motorcycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk
Occupation	Employed	Count	20	20	7	8	3	8	5	1
		% within Age	27.78	27.78	9.72	11.11	4.17	11.11	6.94	1.39
		% within Occupation	20.20	32.26	46.67	13.33	16.67	29.63	83.33	10
	Self employed/ Business	Count	1	5	0	2	0	1	0	1
		% within Age	10	50	0	20	0	10	0	10
		% within Occupation	1.01	8.06	0	3.33	0	3.70	0	10
	Student	Count	73	35	7	48	14	18	1	8
		% within Age	35.78	17.16	3.43	23.53	6.86	8.82	0.49	3.92
		% within Occupation	73.74	56.45	46.67	80	77.78	66.67	16.67	80
	Unemployed	Count	5	2	1	2	1	0	0	0
		% within Age	45.45	18.18	9.09	18.18	9.09	0	0	0
		% within Occupation	5.05	3.23	6.67	3.33	5.56	0	0	0

Table E. 9: Mode of transportation used by travelers according to their occupation in present situation

		Mode							
		Public Bus	Private Car	Motorcycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk

Occupation	Employed	Count	11.00	27.00	6.00	10.00	2.00	6.00	7.00	3.00
		% within Age	15.28	37.50	8.33	13.89	2.78	8.33	9.72	4.17
		% within Occupation	18.33	35.53	40.00	14.29	10.53	21.43	58.33	17.65
	Self employed/ Business	Count	1.00	5.00	1.00	1.00	0.00	1.00	0.00	1.00
		% within Age	10.00	50.00	10.00	10.00	0.00	10.00	0.00	10.00
		% within Occupation	1.67	6.58	6.67	1.43	0.00	3.57	0.00	5.88
	Student	Count	47.00	39.00	8.00	57.00	16.00	21.00	4.00	12.00
		% within Age	23.04	19.12	3.92	27.94	7.84	10.29	1.96	5.88
		% within Occupation	78.33	51.32	53.33	81.43	84.21	75.00	33.33	70.59
	Unemployed	Count	1.00	5.00	0.00	2.00	1.00	0.00	1.00	1.00
		% within Age	9.09	45.45	0.00	18.18	9.09	0.00	9.09	9.09
		% within Occupation	1.67	6.58	0.00	2.86	5.26	0.00	8.33	5.88

Table E. 10: Mode of transportation used by travelers according to their type of residence before lockdown

			Mode							
			Public Bus	Private Car	Motorcycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk
TYPE OF RESID	Residential Building	Count	69	41	11	33	9	13	4	4
		% within Age	37.50	22.28	5.98	17.93	4.89	7.07	2.17	2.17
		% within Type of Residence	67.65	64.06	55	50.77	39.13	40.63	36.36	28.57
	high Rise Apartment	Count	7	16	2	10	2	5	1	3
		% within Age	15.22	34.78	4.35	21.74	4.35	10.87	2.17	6.52
		% within Type of Residence	6.86	25	10	15.38	8.70	15.63	9.09	21.43
	Commercial Building	Count	1	1	0	1	0	0	0	0
		% within Age	33.33	33.33	0	33.33	0	0	0	0
		% within Type of Residence	0.98	1.56	0	1.54	0	0	0	0
		Count	14	0	2	12	7	7	0	1

ENCE	University Hall/ Dormitory	% within Age	32.56	0	4.65	27.91	16.28	16.28	0	2.33
		% within Type of Residence	13.73	0	10	18.46	30.43	21.88	0	7.14
		Count	1	0	0	0	0	1	1	1
	Hostel	% within Age	25	0	0	0	0	25	25	25
		% within Type of Residence	0.98	0	0	0	0	3.13	9.09	7.14
		Count	5	5	5	5	5	5	5	5
	Mess	% within Age	12.50	12.50	12.50	12.50	12.50	12.50	12.50	12.50
		% within Type of Residence	4.90	7.81	25	7.69	21.74	15.63	45.45	35.71
		Count	4	1	0	4	0	1	0	0
	Office Quarter	% within Age	40	10	0	40	0	10	0	0
		% within Type of Residence	3.92	1.56	0	6.15	0	3.13	0	0
		Count	1	0	0	0	0	0	0	0
	Other	% within Age	100	0	0	0	0	0	0	0
		% within Type of Residence	0.98	0	0	0	0	0	0	0

Table E. 11: Mode of transportation used by travelers according to type of residence in present situation

			Mode							
			Public Bus	Private Car	Motorcycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk
TyPE of Reside		Count	39	50	12	42	6	14	11	10
	Residential Building	% within Age	21.20	27.17	6.52	22.83	3.26	7.61	5.98	5.43
		% within Type of Residence	60	67.57	66.67	58.33	28.57	45.16	73.33	52.63
		Count	8	20	1	9	3	2	1	2
	high Rise Apartment	% within Age	17.39	43.48	2.17	19.57	6.52	4.35	2.17	4.35
		% within Type of Residence	12.31	27.03	5.56	12.50	14.29	11.11	6.67	10.53
		Count	0	1	0	1	0	6.45	0	0
	Commercial Building	% within Age	0	33.33	0	33.33	0	1	0	0
		% within Type of Residence	0	1.35	0	1.39	0	33.33	0	0
		Count	9	0	2	14	8	3.23	0	2

nce	University Hall/ Dormitory	% within Age	20.93	0	4.65	32.56	18.60	8	0	4.65
		% within Type of Residence	13.85	0	11.11	19.44	38.10	18.60	0	10.53
		Count	1	0	0	0	0	25.81	0	2
	Hostel	% within Age	25	0	0	0	0	1	0	50
		% within Type of Residence	1.54	0	0	0	0	25	0	10.53
		Count	3	3	3	3	3	3.23	3	3
	Mess	% within Age	12.50	12.50	12.50	12.50	12.50	3	12.50	12.50
		% within Type of Residence	4.62	4.05	16.67	4.17	14.29	12.50	20	15.79
		Count	5	0	0	2	1	9.68	0	0
	Office Quarter	% within Age	50	0	0	20	10	2	0	0
		% within Type of Residence	7.69	0	0	2.78	4.76	20	0	0
		Count	0	0	0	1	0	6.45	0	0
	Other	% within Age	0	0	0	100	0	0	0	0
		% within Type of Residence	0	0	0	1.39	0	0	0	0

Table E. 12: Mode of transportation used by travelers according to place owning before lockdown

			Mode							
			Public Bus	Private Car	Motorcycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk
	Yes	Count	29	36	5	18	4	9	2	3
		% within Age	27.36	33.96	4.72	16.98	3.77	8.49	1.89	2.83
		% within Mode	29.29	58.06	33.33	30	22.22	33.33	33.33	30
	No	Count	70	26	10	42	14	18	4	7
		% within Age	36.65	13.61	5.24	21.99	7.33	9.42	2.09	3.66
		% within Mode	70.71	41.94	66.67	70	77.78	66.67	66.67	70

Table E. 13: Mode of transportation used by travelers according to place owning in present situation

		Mode							
		Public Bus	Private Car	Motorcycle	Rickshaw	Cycle	Ride sharing apps	CNG	Walk
Yes	Count	15	46	7	24	2	6	4	2
	% within Age	14.15	43.40	6.60	22.64	1.89	5.66	3.77	1.89
	% within Mode	25	60.53	46.67	34.29	10.53	21.43	33.33	11.76
No	Count	45	30	8	46	17	22	8	15
	% within Age	23.56	15.71	4.19	24.08	8.90	11.52	4.19	7.85
	% within Mode	75	39.47	53.33	65.71	89.47	78.57	66.67	88.24