A COMPREHENSIVE ANALYSIS OF SOCIO-ECONOMIC AND TRAVEL BEHAVIOR FACTORS INFLUENCING UNIVERSITY STUDENTS MODE CHOICE IN THE DAFFODIL SMART CITY AREA

A thesis submitted in partial fulfillment of the Requirements for the award of a degree of

Bachelor of Science in Civil Engineering

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DECLARATION

The dissertation, titled **" A Comprehensive Analysis of Socio-Economic and Travel Behavior Factors Influencing University Students Mode Choice in the Daffodil Smart City Area** " was completed under the supervision of Mr. Kazi Obaidur Rahman (Assistant professor), Department of Civil Engineering, Daffodil International University, Dhaka, Bangladesh, and was approved in partial fulfillment of the requirement for the capstone project part of the Bachelor of Science in Civil Engineering

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ABSTRACT

This study presents a comprehensive analysis of the socio-economic and travel behavior factors that are usually influence the kind of mode choice to university students in the Daffodil Smart City area of Ashulia sub-urban of Dhaka. As urban expansion through the help of sub-urban surroundings and rising student populations reshape mobility as needs, understanding the determinants of students travel decisions becomes type of crucial for sustainable transport planning as part of sustainable development. Based on previous theories of mode choice and existing empirical research in Dhaka and Toronto, this study explores the state of variables as travel time, cost, distance, etc. Home income, gender, vehicle ownership and possession of a license is everlasting. Influence selection of students among the alternative modes of transport that are available to commute. Firstly, the main survey data were gathered among the students of the university who live and study there studying in or around the Daffodil Smart City campus as similar to Halls. And modelled with discrete choice techniques, such as Multinomial Logit. They are (MNL), Nested Logit (NL) and Cross-Nested Logit (CNL) frameworks. The results disclose that that travel charge, income and time do not merely considerably affect student choices. But also behavioral change and frequency of trips, and socio-economic factors including additional and significant roles in are played by income, gender and vehicle ownership. Selecting mode preferences of eight available modes what can be chosen as mode. As an output of the study, the sensitivity of students tend to is mentioned. Affordability and accessibility, which implies preference of public and non-motorized. Among the lower-income groups. This discovery will provide a useful contribution. To those accountable policy-makers who make policy about such, transport planners, and university administrations wishing to develop inclusive and student-friendly mobility. Policies that enhance sustainability and equitable access of transport modes in the university and local or local modes are available in the emerging urban universities similar to the Daffodil Smart City area.

Keywords: Mode Choice Behavior; University Travel Pattern; Socio-Economic Influences; Travel Cost and Time; Discrete Choice Models; Daffodil Smart City; Transportation Policy

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Transportation systems play a fundamental role in ensuring access to education, employment, and social opportunities in urban areas as well as in sub urban. Among university students, travel mode choice mostly depend on few social and personal thing like affordability, accessibility and how easy or comfortable the trip feels. Understanding and considering these factors is a kind of essential for sustainable development and inclusive transportation policies which is necessary to a city, especially in rapidly urbanizing cities as like Dhaka, Chittagong as well as like sub urban area Daffodil Smart City where population growth and spatial expansion continue to reshape urban mobility type of patterns.

University students are represent a distinct segment or portion of travelers with unique travel needs, demand and constraints. Their decisions are typically influenced by some factors such as like travel time, cost, distance, household income, gender, vehicle ownership, and possession of a driving license ownership. These determinants reflect lifestyle preferences as well as economic capability. In the majority of cases, students have limited time. volume of revenue, they tend to be more perceptive to bear transportation expense and availability. to modes of transport like walking, cycling or public transport that are not expensive.

A number of previous research studies have examined such types of relations but rather slightly. different angles. For example, Islam, Hoque, and Ahmed (2023) studied how university teachers at BUET in Dhaka choose their travel mode, and they found that cost, time, and comfort largely influence their decisions. In a separate piece of research, Rahman and Hoque (2019) looked into how students from private universities in Dhaka travel to their campuses. Their work mainly focus on the daily travel pattern of those students and the things that mostly guide their transport decision.

They observed that a student's income level and the ease of access to transport facilities strongly influence the way they choose to travel. Looking beyond Bangladesh, Hasnine, Habib, and Shalaby (2018) carried out research on university students in Toronto, Canada, and discovered that travel distance, family income, and the frequency of campus visits all play a part in determining the preferred travel mode. All together, these studies are suggested that any type of realistic model of travel behavior needs to consider both economic circumstances and individual behavioral traits.

Based on that background, the area of this research is the Daffodil Smart City in. Ashulia Model Town is a growing town at a rapid rate having numerous universities and various others. kind of travel habit. The study investigates how students' socio-economic traits such as income, gender, and employment status and travel-related factors like cost, time, distance, and vehicle ownership influence their daily mode-choice decisions. The results are expected to offer practical evidence that can guide both policy makers and university authorities in planning more efficient campus transport systems, encouraging sustainable mobility, and reducing inequality in access among students.

1.2 Objective

The main aim of this study is to find out how different socio-economic and travel behavior factors affect the mode choice of university students in Daffodil Smart City area.

This research is mainly guided by few specific objectives given below:

- To find the main factors that influence students' mode choice, specially travel time, cost, distance, gender, vehicle ownership and having a driving license.
- To study the relation between students' financial condition (monthly family income) and their preferred transport mode, and how affordability change the choice between motorized and non-motorized options.
- To look into the changing side of student travel behavior, giving focus on trip frequency and how they switch between modes in their daily travel.
- To make and compare three discrete choice models (MNL, NL and CNL) for understanding how strong these factors are and to find which model better explain students' mode choice behavior.

CHAPTER 2
LITERATURE REVIEW

2.1 Literature Review

Previous research on travel mode choice has consistently shown that both socio-economic conditions and travel behavior factors play an interlinked role in shaping how people decide to travel. For instance, Islam, Hoque, and Ahmed (2023) studied university faculty members at BUET and identified travel cost, time, and comfort as the strongest influences on their mode decisions. In another study, Rahman and Hoque (2019) looked at students from a few private universities in Dhaka to understand how they commute. They noticed that differences in income, the availability of transport, and the cost of using it all shape students' everyday journeys between their homes and campuses. At the same time, in one of the studies, Hasnine, Habib, and Shalaby (2018) examine. observed post-secondary students of Toronto, Canada and reported that the distance they travel. their household income, travel and their visitation to the university are likely to do. determine the type of transportation they depend on. Also observed a similar trend Minal and Mitra (2017) in India, where the safety issues and gender disparities are a concern. significantly influence the daily traveling habit of noticeably affected students. All together, these results shows that mode choice don't depend on only one thing but comes from the mix of personal character and trip related situation.

However, there is still a lack of research in emerging semi-urban educational hubs such as the Daffodil Smart City area, where diverse social backgrounds and rapidly developing transport networks create unique travel behaviors. This study therefore builds upon earlier work by combining socio-economic and behavioral dimensions within discrete choice models—namely the Multinomial Logit (MNL), Nested Logit (NL), and Cross-Nested Logit (CNL)—to gain a deeper understanding of university students' travel mode decisions in the Daffodil Smart City context.

2.2 Variables Influencing Transit Mode Choice

Socio-Economic Factors

├── Gender

├── Monthly Income

├── Working Status

├── Vehicle Ownership

├── License Possession

↓

Travel Behavior Factors

├── **Travel Time**

├── **Travel Cost**

├── **Travel Distance**

├── **Frequency of Campus Visits**

↓

Mode Choice Decision

├── **Transit Mode (Bus, Autorickshaw)**

├── **Active Mode (Walking, Cycling)**

├── **Driving Mode (Private Car, Motorcycle)**

The choice of using public transport is shaped by a mix of service-related and user-related factors. On the service side, variables such as bus or train frequency, waiting time, number of transfers, service reliability, overall travel time (including in-vehicle, waiting, and access or egress time), and fare have consistently been shown to influence passengers' decisions. At the same time, aspects of accessibility for example, the distance to bus stops, route connectivity, and comfort conditions like crowding or the availability of seats play an equally important role. Analyze of Azimi et. al. (2021), indicates that it is the case frequency, cost, and reliability are some of the factors that have a high bearing on transit. ridership, Ranjan (2025) insisted on convenience, demographic. Major factors influencing individual choices of people are characteristics and spatial context. public transport. Socio-economic variables like income, gender and vehicle. ownership has the ability to significantly influence the propensity of an individual to use the public transport. In real life, individuals with their own car or able to acquire one with ease do not use public. cargo that large which demonstrates how the transit system is being substituted by the use of the private vehicles. (Zhang et al., 2023). All in all, both pieces of evidence suggest that both should be taken into account. individual circumstances and conditions of the service in attempting to understand or model. how students make a decision to use public transport or not.

2.3 Variables Influencing Active Transportation Mode Choice

Vigorous mode of transit such as walking or cycling is primarily reliant on myriad of factors. Here, the environment, condition of the road and choice of individual also plays a role. Several factors come into action plus trip distance as well as the availability of safe and continuous sidewalks or cycle. lanes, traffic safety and even the terrain and weather. Where the place of destination is close, walking or cycling is typically easier and more pleasant among the people. Good pedestrian design and frequent maintenance will make a visible change. Elements such as walkways that are well-paved, clearly marked crossings, and traffic-reducing features are common. encourage individuals to walk/cycle more rather than using motorized modes of transport (Active living Research, 2020). The neighborhood construction style also could be real. difference. Neighborhoods that integrate various land uses and streets that are well interconnected. that is, with increased population density tend to have more individuals opting to walk or cycle as part of their daily commuting (Yin et al., 2022). Individual characteristics such as age, Another dimension of influence is gender, health, perceived safety and habitual behavior. The manner in which individuals think about was noted to vary according to Said, Biehl, and Stathopoulos (2020). Their feelings can strongly be determined by convenience, social image, and the effort they need. about walking or cycling. Judging the context at large, the choice to walk or ride. distinctively seldom is by distance alone. It also is determined by the feeling of the surroundings to a. individual and the feeling of attachment that they develop with their immediate surroundings.

2.4 Variables Influencing Driving Mode Choice

Most individuals prefer to drive whether using a motorcycle or a personal car because of reasons that are not known. They tend to confuse economic factors, time pressure and the mere convenience that personal travel. brings. There are numerous other considerations, such as the cost of fuel, parking fees and space, etc. time of total travel (jam time), comfort on trip and door to door. convenience that personal car provides. Under the conventional four-step transportation structure. These points are considered to be a part of the generalized cost that (MWCOG, 2020). establishes the demand of automobiles. Being able to have a car and be a driver. license also are significant facilitators of this mode choice, as they have a direct impact on how. it is accessible driving in fact (Harbering et al., 2020). Otherwise socio-economic background, too. matters. Individuals who have better incomes, are able to work or have bigger families tend to be able to afford private. more convenient to keep and hence comes into more frequent use. At the same time, the road setting operates by such parameters as the level of connectivity of the network, traffic, the amount of. how convenient it all is, and the predictability of the travel time depends on the availability of parking, as well as the predictability of the travel time. convenient driving seems. Zhang et al. (2023) also mentioned that individuals in higher. income groups tend more to the private modes since they are able to afford. the price and should be more comfortable. In short, the decision to drive is normally made by two. main procures the financial power to possess it and the real convenience that good. facilitates by means of transport infrastructure.

CHAPTER 3
METHODOLOGY

3.1 Modelling Formulation and Mathematical Representation

The purpose of this study was twofold. **First,** to find out which factors influence how students choose their mode of transportation. **Second,** to better understand the changing patterns of how they travel.

To complete these objectives, three discrete choice models were used Multinomial Logit (MNL), Nested Logit (NL) and Cross-Nested Logit (CNL). These models illustrate the underlying reasons behind students' choices of travel mode by relating their decisions to a range of personal and travel-specific factors. Such factors include travel time, travel cost, distance, income, gender, driving license and vehicle ownership, age, employment status, and the frequency of their trips.

3.2 Multinomial Logit (MNL) Model

The Multinomial Logit Model (MNL) assumes that each individual $n$chooses an alternative i(mode of transport) that provides the highest utility.
The total utility $U_{in}$is composed of a deterministic part $V_{in}$and a random error term ε_{in}:

$$U_{in} = V_{in} + \varepsilon_{in}$$

where the systematic utility function is expressed as:

$$\begin{aligned} V_{in} = \beta_0^{(i)} + \beta_t\, Time_{in} + \beta_c\, Cost_{in} + \beta_d\, Distance_{in} + \beta_{inc}\, Income_n \\ + \beta_{gen}\, Gender_n + \beta_{lic}\, License_n + \beta_{veh}\, Vehicle_n + \beta_{wrk}\, Working_n \\ + \beta_{age}\, Age_n + \beta_{freq}\, Frequency_n \end{aligned}$$

Here, one alternative is taken as the base mode with its intercept $\beta_0 = 0$.

The probability that student $n$chooses mode $i$is:

$$P_{in} = \frac{\exp{(V_{in})}}{\sum_{j \in C} \exp{(V_{jn})}}$$

The estimated coefficients (β) and their p-values highlight how strongly each factor affects students choice of transport mode choise and the direction of that type of effect. Factors with negative coefficients like travel cost and travel time tend to discourage students from choosing that particular mode, as higher costs or longer trips usually make the option less appealing. In contrast, variables with positive coefficients such as income and vehicle ownership enhance the probability of choosing motorized modes. Overall, the model fulfill and support the first objective of this study quite well.

3.3 Nested Logit (NL) Model

The Nested Logit Model (NL) extends MNL by allowing correlation among alternatives that belong to similar mode groups or "nests."
In this study, the modes were grouped into three nests:

- **Active modes:** Walking, Bicycle
- **Driving modes:** Motorcycle, Private Car
- **Transit modes:** Bus, Auto Rickshaw, Leguna, Others

For each mode $i$belonging to nest n:

$$U_{i|n} = V_{i|n} + \varepsilon_{i|n}, 0 < \mu_n \leq 1$$

The *inclusive value* (logsum) for nest $n$is defined as:

$$IV_n = \ln\left(\sum_{j \in C_n} \exp\left(\frac{V_{j|n}}{\mu_n}\right)\right)$$

The conditional probability of choosing mode $i$given nest $n$is:

$$P(i \mid n) = \frac{\exp\left(\frac{V_{i|n}}{\mu_n}\right)}{\sum_{j \in C_n} \exp\left(\frac{V_{j|n}}{\mu_n}\right)}$$

and the probability of selecting nest n:

$$P(n) = \frac{\exp\left(W_n + \mu_n IV_n\right)}{\sum_{m \in N} \exp\left(W_m + \mu_m IV_m\right)}$$

Therefore, the overall probability of choosing mode $i$is:

$$P_i = P(n) \times P(i \mid n)$$

The dissimilarity parameter $\mu_n$$(0 < \mu \leq 1)$ measures the correlation among alternatives within the same nest.

This parameter helps identify dynamic behavioral similarity supporting **Objective 2**—while the estimated coefficients (β) continue to explain influential factors as in **Objective 1**.

3.4 Cross-Nested Logit (CNL) Model

The Cross-Nested Logit (CNL) model further generalizes NL by allowing certain alternatives to belong partially to multiple nests.
For example, *Auto Rickshaw* may be partly associated with both *Driving* and *Transit* groups.
The membership of mode $i$in nest $n$is represented by an allocation parameter α_{in}, where $0 \leq \alpha_{in} \leq 1$and $\sum_n \alpha_{in} = 1$.

The probability of choosing mode $i$is expressed as:

$$P_i = \frac{\exp\left(\frac{V_i}{\mu}\right) \sum_{n \in N} \alpha_{in} S_n^{\frac{\mu}{\mu_n} - 1}}{\sum_{k \in C} \exp\left(\frac{V_k}{\mu}\right) \sum_{n \in N} \alpha_{kn} S_n^{\frac{\mu}{\mu_n} - 1}}$$

where

$$S_n = \sum_{j \in C} \alpha_{jn} \exp\left(\frac{V_j}{\mu_n}\right)$$

and $\mu_n$denotes the dissimilarity parameter for nest n.
This model captures cross-correlation and overlapping travel behavior among alternatives, addressing **Objective 2** by reflecting flexible and mixed travel patterns of university students.

CHAPTER 4
DATA COLLECTION AND ANALYSIS

4.1 Survey Implementation

This paper aimed to learn about the way students of universities make decisions on their daily commuting. modes and what makes them and what influences them. To that end, we assembled an Internet-based. questionnaire named "A Comprehensive Analysis of Socio-Economic and Travel behavior Factors Influencing University Students Mode Choice in Daffodil Smart city area". It was constructed in Google Forms and contained questions that concerned the personal. background and day trips, as students were to explain how they normally travel. when choosing a mode, what is most important. The survey reached students in two different ways. First, the form link went around online shared in university group chats, social-media study circles, and through direct messages between classmates. Then, a QR code connected to the same form was printed and placed on notice boards across Daffodil Smart City and nearby universities. Anyone could scan it on their phone and fill it out within minutes.

That small step made it easier for students to join in and, as a result, brought in a much higher number of responses. very participant completed the survey by choice and without any reward.
All answers were kept anonymous so that privacy and ethical practice could be maintained.
The form included about ten key questions meant to gather the basic socio-economic details and travel habits of the students who took part, as listed below:

- **Name** (collected for response validation, anonymized during analysis)
- **Gender**
- **Age** (in years)
- **Distance** from current residence to university (in kilometers)
- **Main mode of transport** used to travel to university
- **Travel time** from accommodation to university (in minutes)
- **Average daily transportation cost** for university trips (in Bangladeshi Taka)
- **Possession of driving license**
- **Vehicle ownership** at current location
- **Working status** (student only or part-time employed)
- **Average monthly household income** (in Bangladeshi Taka)

When this study was being prepared, the list of variables grew out of ideas noted in earlier works. Only those that really seemed helpful in explaining how students decide on their day-to-day travel were kept for the analysis. In the end, the survey produced 1,024 usable responses from students of many different social and economic groups within the Daffodil Smart City area, each showing their own way of travelling. Later, the answers were arranged in an Excel sheet and then used for the main analysis of this research, which applied the MNL, NL, and CNL models to examine students' travel-mode behaviour in detail.

4.2 Descriptive Statistics

In the initial phase of interpreting our data on the topic we are undertaking, we shall have a few. A summary and a visualization of the how we were summarized using descriptive statistical techniques. collected information. Most of the methods were the impetus behind the analytical approach. on the studentmoveto.ca research portal shared research provide a clear framework to. apprehend travel behaviour in students using basic descriptive statistics. Based on that, there were calculations such as frequency distribution, percentage, and central tendency. (mean and median) to determine the general trend, demographic information, and mode of transportation. tendencies of the university students of Daffodil Smart City area. The next part describe the procedure we used to undertake the descriptive analysis of our data:

Gender Distribution

The samples are predominantly male which is somewhat gender biased. This may somehow influence mode choice: it is possible that the female students would like to use a different mode due to safety or comfort considerations. give more weight to safety and cost.

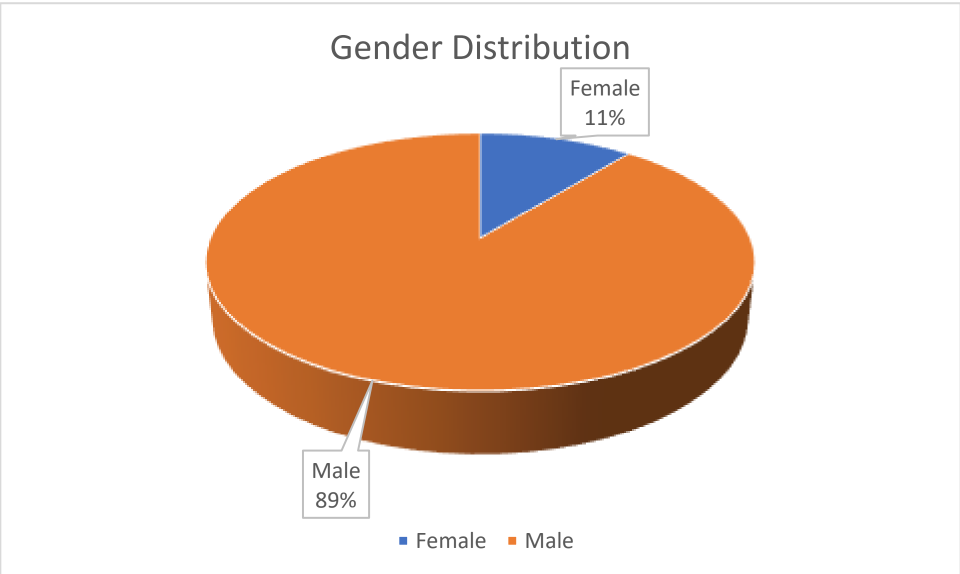

Fig 4.1: Gender Distribution

2. Age Distribution

The age of the majority of these students in this study is 20 to 25 years, thus mostly. undergraduates. Students aged less are more likely to walk or ride bikes whereas older students are more likely to walk. one uses bus or auto rickshaw to move about on a day to day basis.

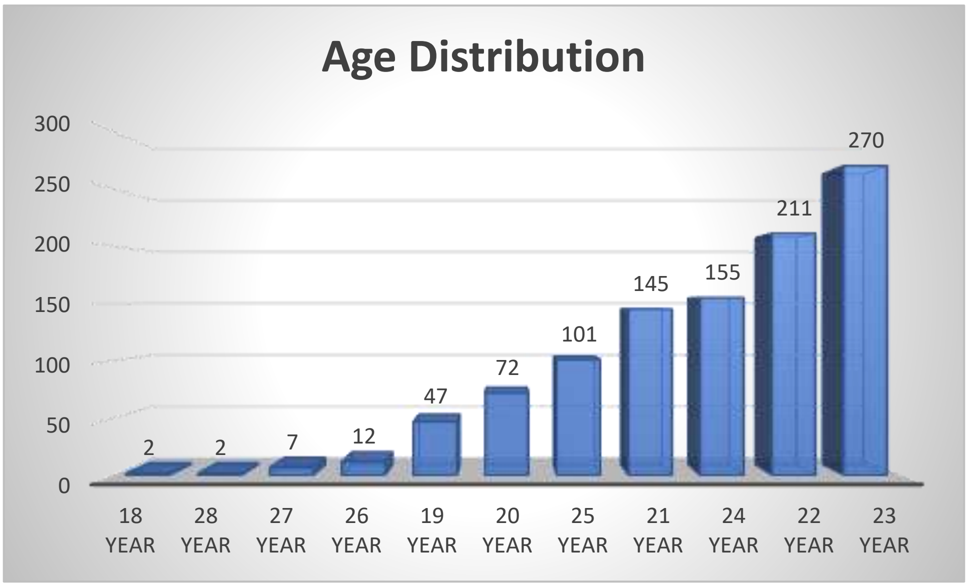

Fig 4.2: Age Distribution

3. Distance to University

The distance is in line with 60 percent of students who travel less than 10 minutes. distribution. The number of students who spend over 30 minutes is very low, which supports short commuting.

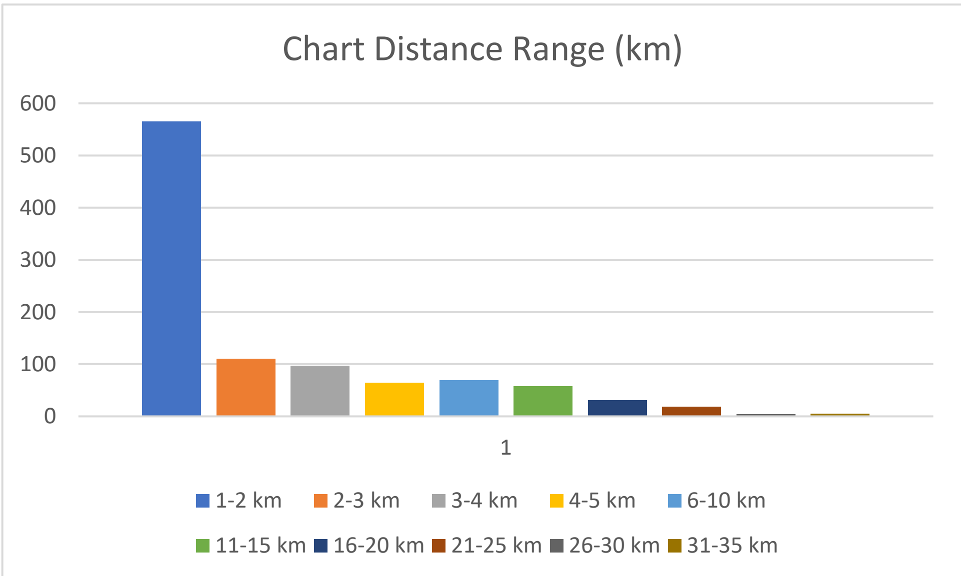

Fig 4.3: Distance to University

4. Mode of Transport

Walking is the most used mode, as the distance of traveling is short and low. cost. The secondary modes are auto rickshaw and bus whereas the minimal modes are the private modes.

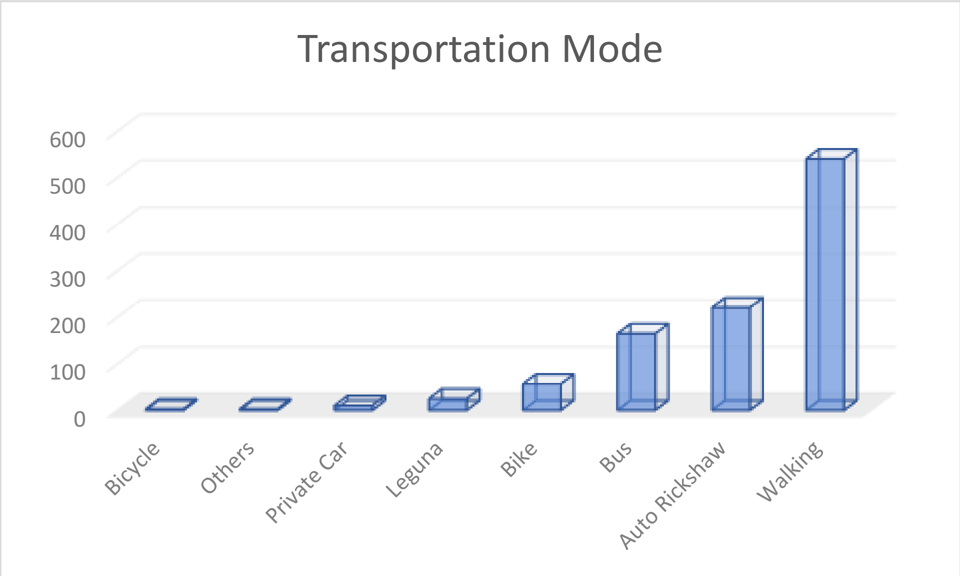

Fig 4.4: Mode of Transport

5. Travel Time

The distance is in line with 60 percent of students who travel less than 10 minutes. distribution. The number of students who spend over 30 minutes is very low, which supports short commuting.

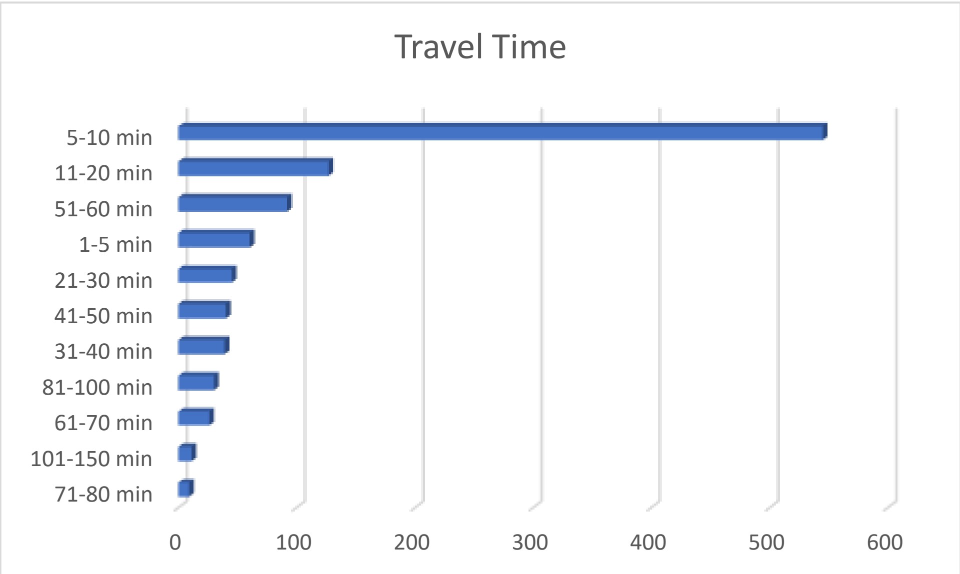

Fig 4.5: Travel Time

6. Daily Transportation Cost

Massive amount of participants spend 0 taka for their daily transportation cost which is 484 person as count from 1024 from all participants and secondly 178 within 30 taka par day.

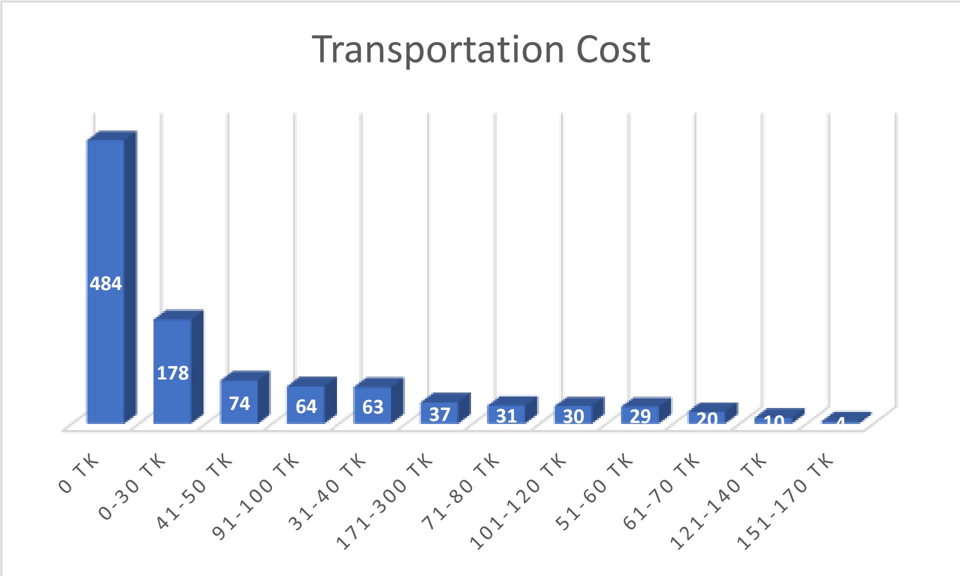

Fig 4.6: Daily Transportation Cost

7. Driving License Ownership

Almost 85 percent of the students do not have any driving license that makes it difficult. them to take personal motorized means.

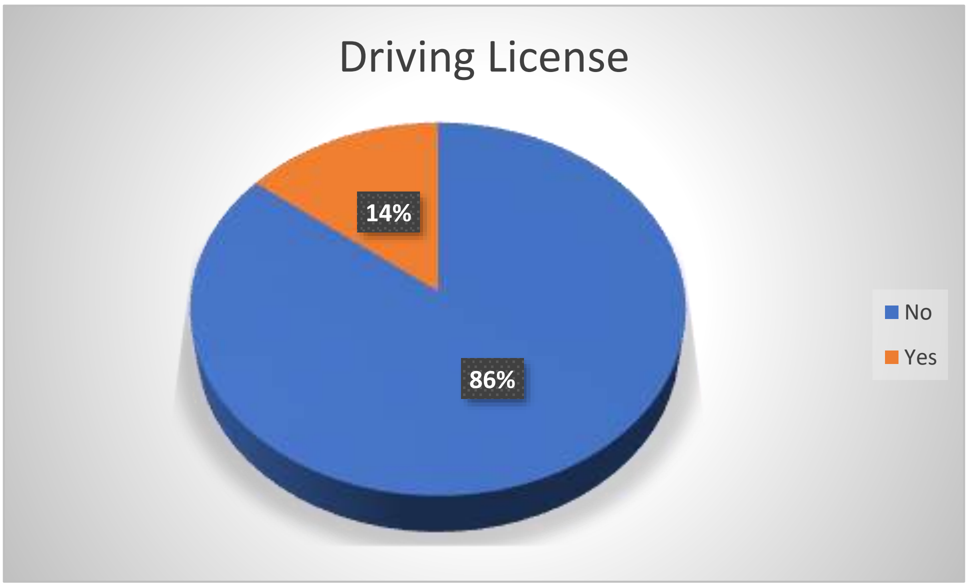

Fig 4.7: Driving License Ownership

8. Vehicle Ownership

The majority of the students also do not have any vehicle and this also explain why walking. and motor transport are the primary option of majority.

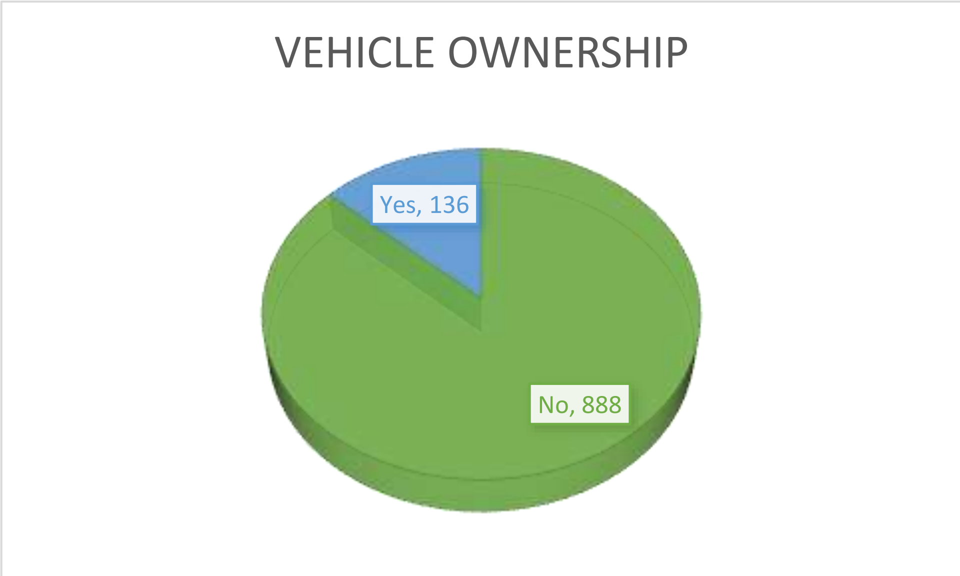

Fig 4.8: Vehicle Ownership

9. Working Status

The larger constituent of the respondents does not work hence low or no income of. their own. This causes them to rely on the cheap means such as walking or bus to get their daily travel.

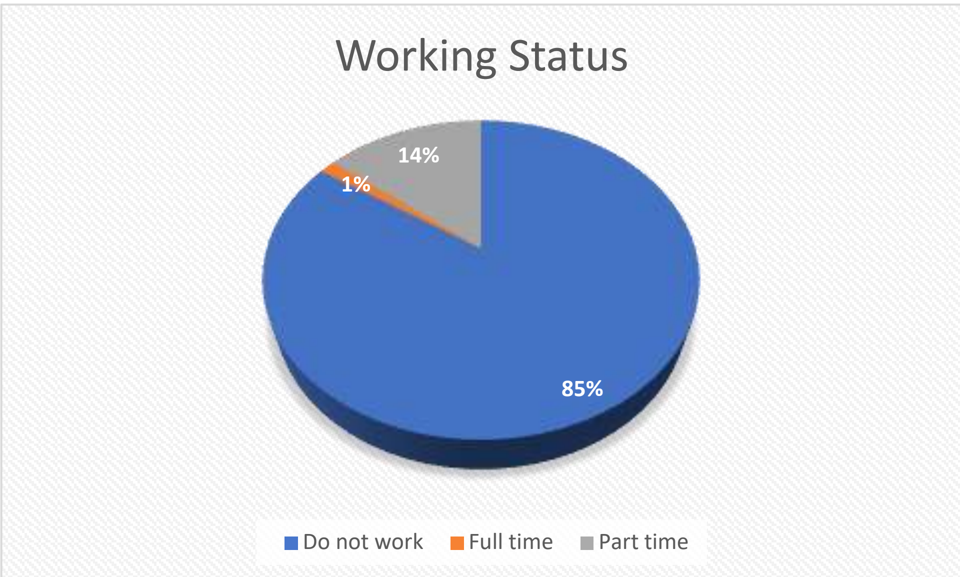

Fig 4.9: Working Status

10. Household Income

A majority of the households make 40-80k per month showing middle-income families. Income is involved in mode affordability and possible access to personal modes

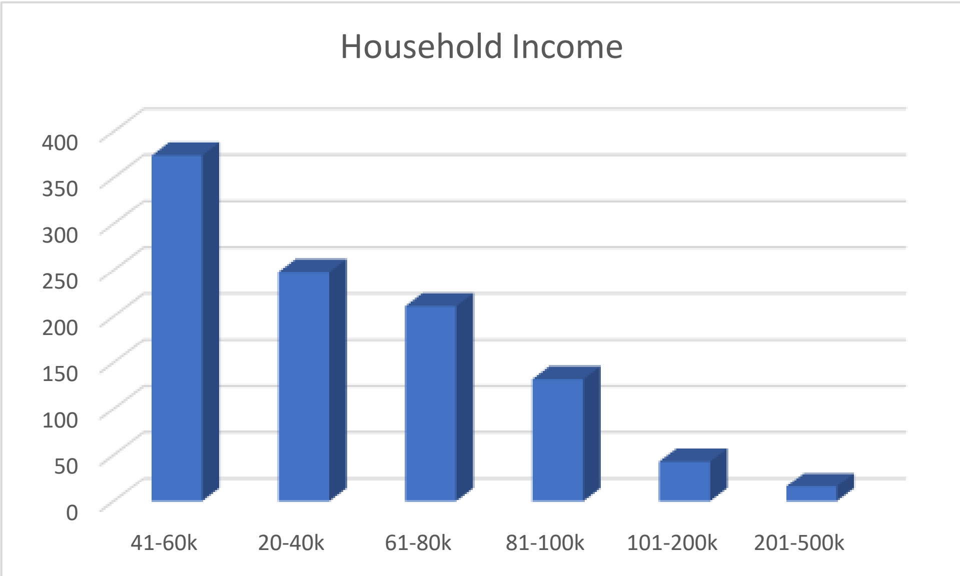

Fig 4.10: Household Income

4.3 Overall Discussion

Based on the charts, it is evident that the students are mainly young. middle income families and reside quite near to the university. Walking appears as the the primary mode of transport of most of them is also due to the fact that it is cheap, vehicles are not readily transported. clear and the distance to travel is limited. Time and out of pocket cost are tolling on. students' mode decisions. Comparatively, there is a signal of gender, income, and employment. social economic factors that drive decisions towards specific directions. Viewed together, the findings support the idea of student transport schemes that consider both the individual situation. and the conditions of travelling that students experience.

4.4 Descriptive Analysis of Transportation Mode

The descriptive statistics of transport modes portrayed the general preferences in terms of transportation of 1,024 university students who commute to the Daffodil Smart City campus. Among all the respondents, walking found as the most common mode, chosen by around 540 students (52.7%). It shows that most of them live in short distance from the university. The second popular mode is Auto Rickshaw, used by about 221 students (21.6%), and then Bus by 165 students (16.1%). Together these three modes cover more than 90% of all responses, showing the high dependency on non-motorized or shared transport for everyday trip.

A smaller number of students reported using Bike (57; 5.6%) and Leguna (25; 2.4%), which are mostly semi-motorized and local shared vehicles. Private car users are very few, only 10 students (1.0%), and only 3 said Bicycle and 3 said Others as their main travel mode. This clearly show that most students don't rely much on personal or alternative transport. Based on these findings, the dataset was categorized into three broader mode groups for subsequent model estimation:

- **Active Modes:** Walking, Bicycle
- **Driving Modes:** Bike, Private Car
- **Transit Modes:** Bus, Auto Rickshaw, Leguna, Others

To further understand the spatial characteristics of student travel, the **route and access network** used by students were identified from the official transportation route map of **Daffodil International University**. The reference map was collected from the university's official transportation section website (https://daffodilvarsity.edu.bd/article/transport) and visually represented below to illustrate the major corridors and catchment areas connecting students' residential zones to the Daffodil Smart City campus. Considering the bellow presentation of transportation modes through google custom map routes that is usually use by students to commute DSC are given bellow:

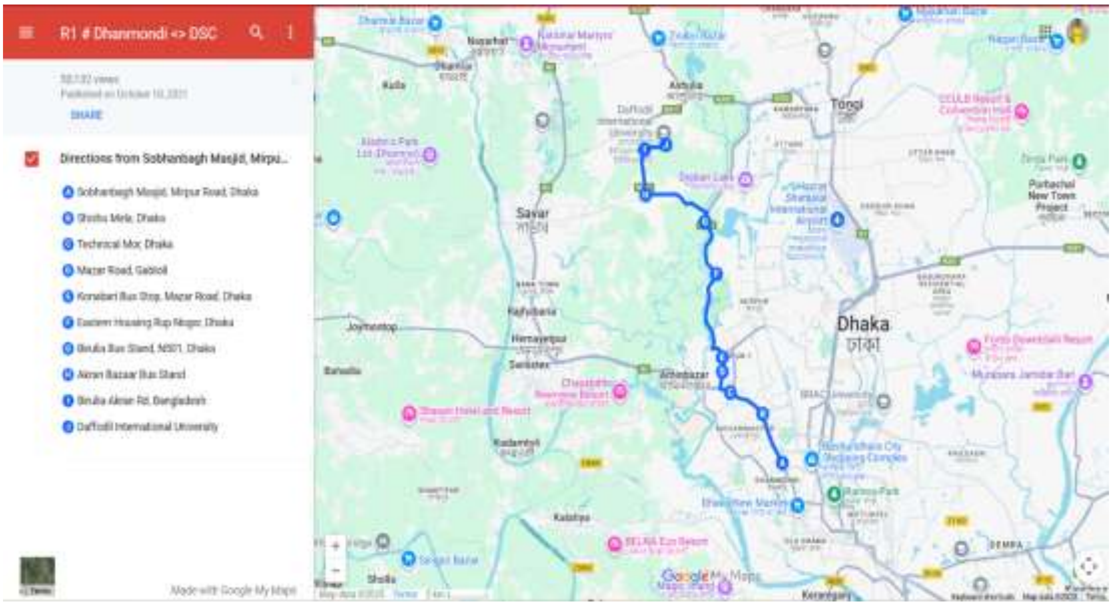

Figure 4.11: Transportation routes from Dhanmondi is connecting Daffodil Smart City (DSC)

This route is one of the key commuting corridors used by students traveling from the Dhanmondi and adjacent zones to the DSC campus. A significant portion of these students primarily use "**Active Modes:** Walking, Bicycle" "**Driving Modes:** Bike, Private Car” **“Transit Modes:** Bus, Auto Rickshaw, Leguna, Others”, which corresponds to the higher frequencies shown in the transportation-mode bar chart.

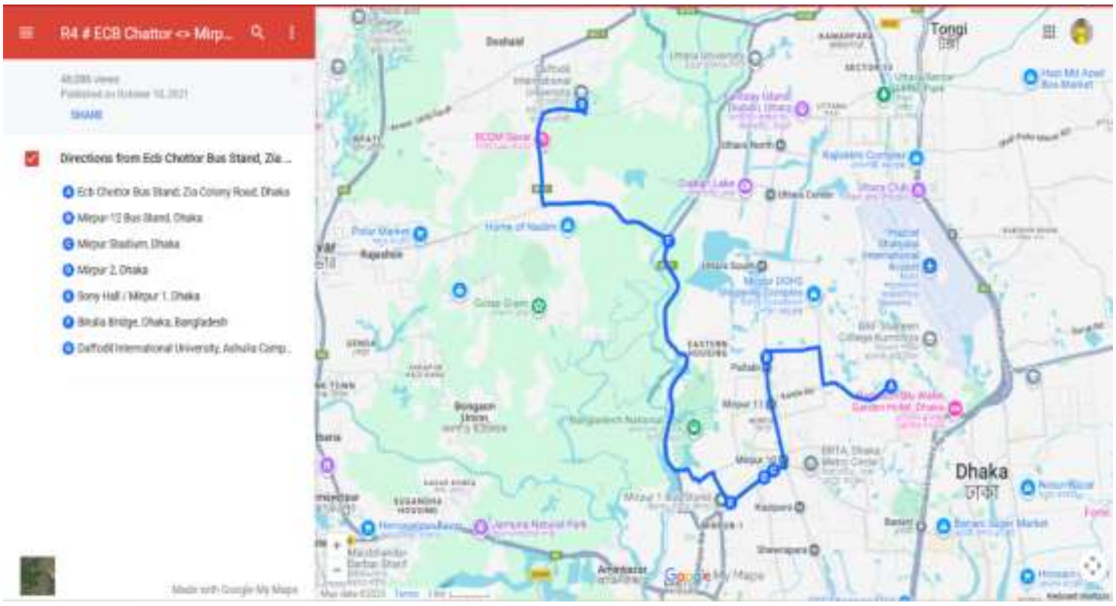

Figure 4.12: Transportation routes from ECB is connecting Daffodil Smart City

This route is one of the key commuting corridors used by students traveling from the ECB (Mirpur) and adjacent zones to the DSC campus. A significant portion of these students primarily use “**Active Modes:** Walking, Bicycle**” “Driving Modes:** Bike, Private Car” **“Transit Modes:** Bus, Auto Rickshaw, Leguna, Others”, which corresponds to the higher frequencies shown in the transportation-mode bar chart.

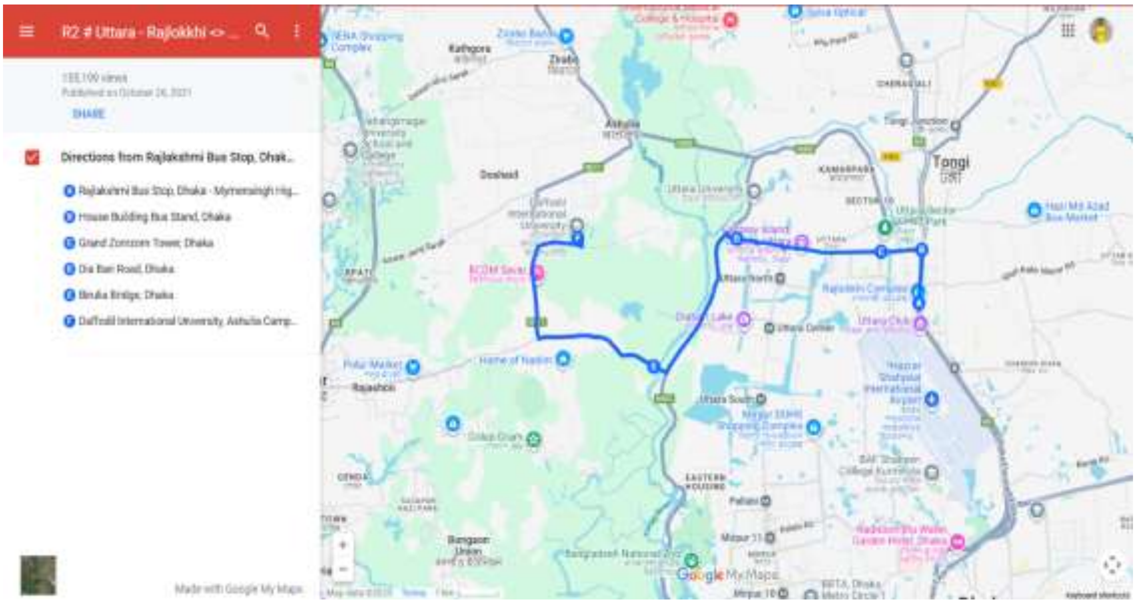

Figure 4.13: Transportation routes from Uttara is connecting Daffodil Smart City

This route is one of the key commuting corridors used by students traveling from the Uttara and adjacent zones to the DSC campus. A significant portion of these students primarily use "**Active Modes:** Walking, Bicycle**"** **"Driving Modes:** Bike, Private Car**"** **"Transit Modes:** Bus, Auto Rickshaw, Leguna, Others**"**, which corresponds to the higher frequencies shown in the transportation-mode bar chart.

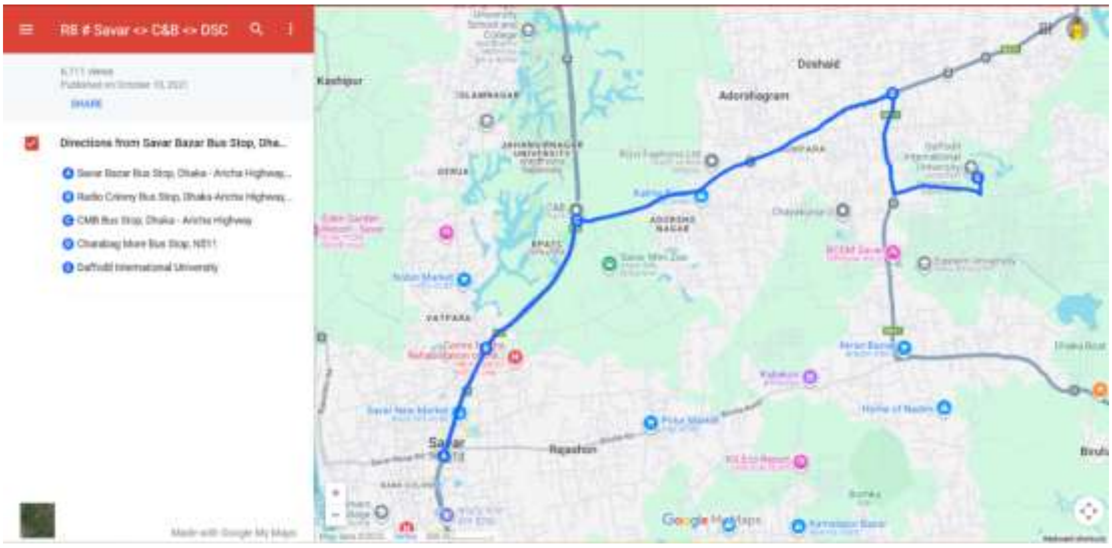

Figure 4.14: Transportation routes from Savar is connecting Daffodil Smart City

This route is one of the key commuting corridors used by students traveling from the Savar and adjacent zones to the DSC campus. A significant portion of these students primarily use "**Active Modes:** Walking, Bicycle**"** **"Driving Modes:** Bike, Private Car**"** **"Transit Modes:** Bus, Auto Rickshaw, Leguna, Others**"**, which corresponds to the higher frequencies shown in the transportation-mode bar chart.

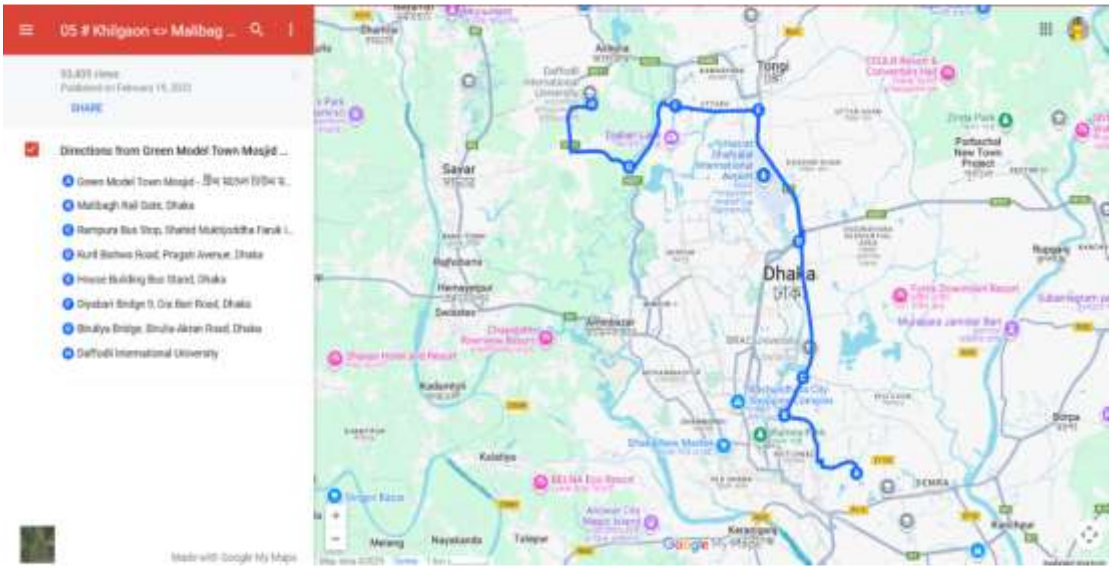

Figure 4.15: Transportation routes from Khilgaon is connecting Daffodil Smart City

This route is one of the key commuting corridors used by students traveling from the Khilgaon and adjacent zones to the DSC campus. A significant portion of these students primarily use “**Active Modes:** Walking, Bicycle**” “Driving Modes:** Bike, Private Car” **“Transit Modes:** Bus, Auto Rickshaw, Leguna, Others**”**, which corresponds to the higher frequencies shown in the transportation-mode bar chart.

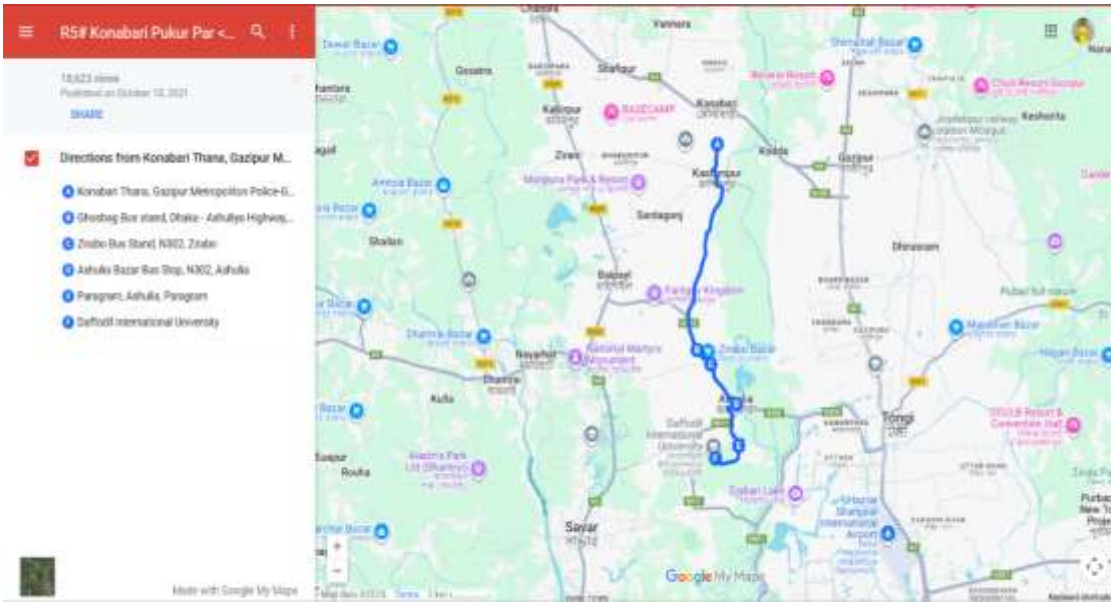

Figure 4.16: Transportation routes from Konabari is connecting Daffodil Smart City

This route is one of the key commuting corridors used by students traveling from the Konabari and adjacent zones to the DSC campus. A significant portion of these students primarily use “**Active Modes:** Walking, Bicycle**” “Driving Modes:** Bike, Private Car” **“Transit Modes:** Bus, Auto Rickshaw, Leguna, Others**”**, which corresponds to the higher frequencies shown in the transportation-mode bar chart.

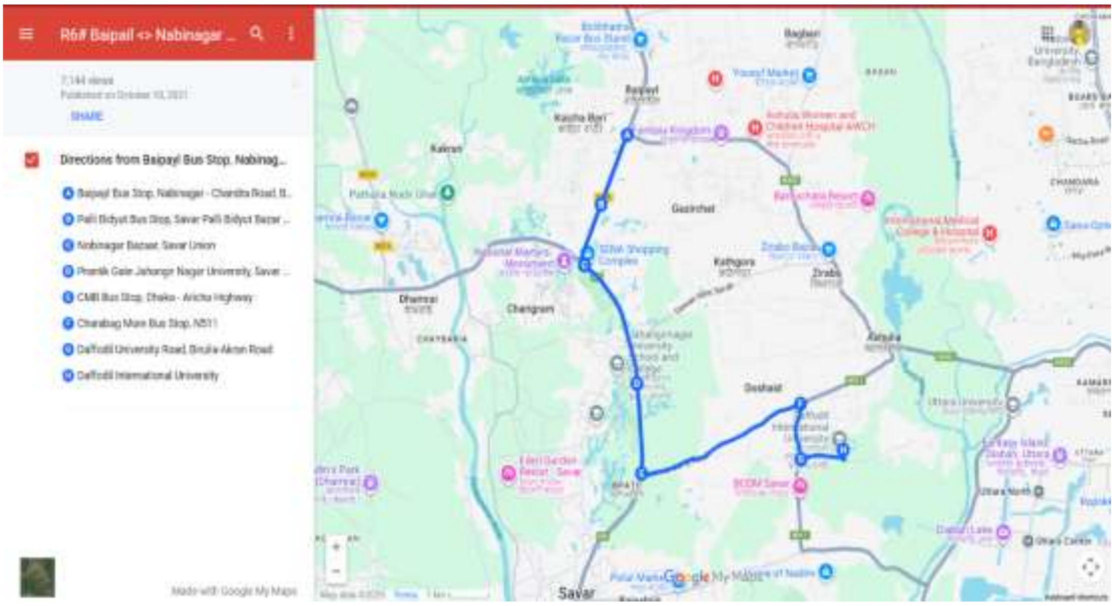

Figure 4.17: Transportation routes from Baipail is connecting Daffodil Smart City

This route is one of the key commuting corridors used by students traveling from the Baipail and adjacent zones to the DSC campus. A significant portion of these students primarily use “**Active Modes:** Walking, Bicycle**” “Driving Modes:** Bike, Private Car**” “Transit Modes:** Bus, Auto Rickshaw, Leguna, Others**”**, which corresponds to the higher frequencies shown in the transportation-mode bar chart.

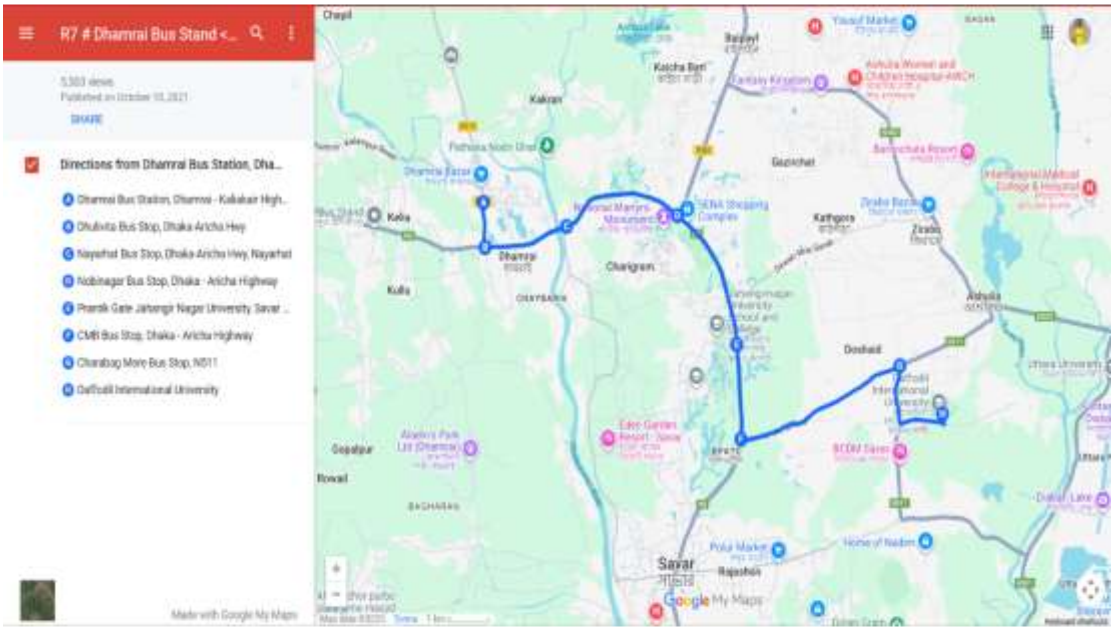

Figure 4.18: Transportation routes from Dhamrai is connecting Daffodil Smart City

This route is one of the key commuting corridors used by students traveling from the Dhamrai and adjacent zones to the DSC campus. A significant portion of these students primarily use “**Active Modes:** Walking, Bicycle**” “Driving Modes:** Bike, Private Car**” “Transit Modes:** Bus, Auto Rickshaw, Leguna, Others**”**, which corresponds to the higher frequencies shown in the transportation-mode bar chart.

4.5 Identify the Factors that Influence the Choice of Transportation Mode

To find out which factors play the strongest role in shaping how university students choose their mode of travel, a detailed analysis was carried out using the survey data from 1,024 respondents. The main purpose of this stage was to see how both socio-economic traits and travel-related aspects affect students’ decisions when commuting to the Daffodil Smart City campus. In this analysis, the dependent variable referred to the primary mode of transport students used to reach the university. Personal and trip factors are independent variables that were examined to explain the influence of these independent variables on the choices students make in terms of travel mode. The following are the variables applied in this objective:

Dependent Variable:

- Which main mode of transport do you use to travel to University?

Independent Variables:

1. Time required to travel from accommodation to university
2. Average daily transportation cost for travelling to university
3. Distance from current location to university
4. Possession of driving license
5. Vehicle ownership
6. Gender
7. Age
8. Average monthly household income
9. Working status

These variables, taken together, reflect the primary variables that influence student choice. their travel modes. In order to analyze their impact in a closer detail, discrete choice models. as well as the Multinomial Logit (MNL), the Nested Logit (NL) and the Cross-Nested Logit. (CNL) were applied. The connections between the independent are made through these models. To identify the factors, variables and the mode of transport chosen were analysed. have the greatest influence on the travelling behaviour of students.

4.6 Objective Summary and Analytical Framework

The study was informed by two main objectives that informed the whole research. analytical model estimation process. All of the objectives were associated with. a set of certain analytical objectives and model results, which are presented below:

Table: 4.1 Analytical Goal & Related Model Output

Objective	Analytical Goal	Related Model Output
Objective 1: To find out the main factors that affect how students choose their modes of transport and to observe how their financial situation and how financially they are doing. (like monthly income) relates with their mode choice decision.	This part mainly look at how various things such as traveling. time, travel cost, income, gender, vehicle ownership and having a driving license influence the way students choose their travel mode.	Estimated coefficients (β), p-values, and marginal effects.
Objective 2: Understand the dynamic aspects of student travel habits (e.g., frequency of campus visits).	Analyze behavioral variations arising from travel frequency, accessibility, and overlapping correlations among similar travel modes.	Nest coefficients (μ), inclusive values, and utility structure derived from nested or cross-nested logit models.

These objectives were achieved with the help of three discrete choice models- Multinomial Logit. They include (MNL), Nested Logit (NL) and Cross-Nested Logit (CNL). Each of these models give various type of analytical comprehension and output parameters which assists in elucidating. behave the students to travel in a better manner.

Table: 4.2 Outputs to Report & Linked Objective

Model	Outputs to Report	Linked Objective(s)
MNL	β (coefficients), p-values, Pseudo R^2, marginal effects	Objective 1
NL	β, p-values, μ (inclusive value), nested log-likelihood	Objectives 1 & 2
CNL	β, p-values, μ/α (cross-nesting parameters), Pseudo R^2	Objectives 1 & 2

In short, Objective 1 mainly focus on estimating the coefficients (β) and p-values to find out which factors have a real impact on students' mode choice, giving more

attention on income, cost, and travel time.
On the other hand, Objective 2 put more focus on estimating the nesting (μ) and cross-nesting (α) parameters to understand how some travel modes are connected or overlap with each other, showing the flexible and related nature of students' daily travel habit.

4.7 Multinomial Logit (MNL) Model Results and Interpretation

The Multinomial Logit (MNL) model was estimated to identify the factors influencing students' transportation mode choice.
The base alternative considered in this model was Walking, while other modes such as Auto Rickshaw and *Bike* were compared against it.
The estimation was performed using Maximum Likelihood Estimation (MLE) with 1,024 total observations and a pseudo R^2 value of **0.3385**, indicating a reasonably good model fit for behavioral data.

Key Findings:

1. **Significant Variables ($p < 0.05$):**

    - **Travel Time (β = -0.1166, p = 0.0153)**
      Travel time shows a negative and statistically significant link with the chance of choosing Bike or Auto Rickshaw.
      This means, when the travel time gets longer, students are less likely to use these modes and prefer walking instead.

    - **Travel Cost (β = -0.0836, p = 0.0083)**
      Higher daily travel cost also make students not so interested to use the paid or motorized transport.
      Most of them goes for walking or other active mode when the cost become high.

    - **Income (β = +0.0329, p = 0.0028)**
      Monthly family income have a positive and significant impact, means students from higher income family use motorized modes like Auto Rickshaw or Bike instead walking are more likely to.

    - **Age (β = -0.8536, p = 0.004)**

      The negative coefficient show that younger students more likely to walk, while older ones usually shift toward motorized options.

2. **Non-significant Variables ($p > 0.05$):**

3. Gender, License Ownership, Vehicle Ownership, and Working Status
   These variables show no significant impact, means they didn't change the chance of mode choice much in this sample.

4. **Coefficient Direction and Behavioral Meaning:**
   - Negative coefficients (for Time and Cost) shows disutility when these factors increase, the chance of choosing that mode going down slowly.
   - Positive coefficients (for **Income** and **Vehicle Ownership**) increase the probability of choosing motorized modes, aligning with real-world expectations.

5. **Model Fit Indicators:**
   - **Pseudo R^2 = 0.3385** indicates that approximately 33.8% of the variation in mode choice is explained by the model.
   - **Log-Likelihood = -560.24** and **LL Ratio p-value < 0.001** confirm that the overall model is statistically significant.

Interpretation Linked to Objectives

- **Objective 1:** Identify the factors that influence the choice of transportation mode.
  The significant coefficients for **Travel Time, Travel Cost, Income, and Age** directly address this objective.
  These variables show clear and statistically significant influence on students' transportation choices shorter travel time, lower cost, and higher income notably increase the likelihood of selecting motorized modes.

- **Objective 2:** Understand dynamic travel habits (frequency of campus visits):
  While frequency was added in the model, it was not found significant in MNL, which mean the dynamic travel behavior or regular mode switching maybe not fully captured under the IIA assumption.
  So, this objective is better handled in Nested Logit (NL) and Cross-Nested Logit (CNL) model that can deal with correlation or overlap among different travel modes.

Table: 4.3 MNL Analytical Goal & Related Model Output

Summary of MNL Findings:

Variable	Coefficient (β)	p-value	Interpretation
Travel Time	−0.1166	0.015	Longer travel time reduces likelihood of choosing Bike/Auto Rickshaw
Travel Cost	−0.0836	0.008	Higher cost discourages motorized mode choice
Income	+0.0329	0.0028	Higher income increases probability of choosing motorized modes
Age	−0.8536	0.004	Younger students prefer walking
Gender, License, Vehicle, Working	—	>0.05	Statistically insignificant

Discussion (Objective 1 Achieved):

The MNL model successfully identifies that **travel time, cost, income, and age** are the most influential factors affecting students' transportation mode choice in the Daffodil Smart City area.

However, since the model assumes independence of irrelevant alternatives (IIA), the dynamic and correlated behavior patterns among similar modes are further examined in the **NL** and **CNL** models to address **Objective 2**.

4.8 Nested Logit (NL) Model Results and Interpretation

The Nested Logit (NL) model was estimated to overcome the independence of irrelevant alternatives (IIA) limitation of the MNL model and to capture correlation among similar travel modes.

The alternatives were classified into three **nests** based on mode characteristics:

- **Non-Motorized (Active):** Walking, Bicycle
- **Public (Transit):** Bus, Auto Rickshaw, Leguna
- **Private (Driving):** Bike, Private Car

The model was calibrated using 1,024 observations.
The **log-likelihood** value at convergence was **–2041.10**, and the **pseudo-R^2 = 0.655**, which indicates a substantial improvement in model fit compared to the MNL model (pseudo-R^2 = 0.3385).

Table: 4.4 NL Coefficient (β) p-value Interpretation

Key Coefficients and Significance

Variable	**Coefficient (β)**	**p-value**	**Interpretation**
Travel Cost (B_COST)	+0.0067	0.000	Statistically significant; as cost increases, probability of choosing low-cost public/active modes rises.
Distance (B_DIST)	+0.0334	0.000	Positive and highly significant; longer distances encourage the use of motorized modes.
Income (B_INC)	+0.0334	0.000	Significant; higher-income students prefer private or faster modes.
Gender (B_MALE)	+0.0334	0.000	Male students more likely to select motorized options.
LAMBDA_Public (μ ≈ 0.937)	—	—	Inclusive value within $0 < \mu < 1$ indicates moderate correlation among public transit alternatives.
LAMBDA_Private (μ ≈ 0.900)	—	—	High correlation among private modes (bike, car) — behavioral similarity evident.
LAMBDA_NonMotor (μ ≈ 0.933)	—	—	Active modes (walking/bicycle) share strong similarity.

Interpretation and Objective Linkage

Objective 1 – Influential Factors:
The NL model again confirm the result from MNL, showing that income, cost, distance and gender are important factors for students' mode choice.
Students with higher income and longer trip distance mostly prefer motorized mode, but those who face higher daily cost more likely to choose cheaper and non-motorized one.

Objective 2 – Dynamic Travel Behavior:
The inclusive-value (λ / μ) parameters measure the correlation and behavioral link inside each nest. All three μ value (0.90 – 0.94) stay between 0 and 1, which follow the theory and confirm that there is some relation inside same nest.
This mean students see options like bus and auto-rickshaw as partly substitute, showing their flexible and dynamic travel habit.
So, the NL model can capture better how students switch between same type of mode depending on travel situation or how often they go campus.

Model Fit Summary

Indicator	**Value**
Log-Likelihood	–2041.10
Null Log-Likelihood	–655.26
Pseudo R^2	0.655
AIC / BIC	4110.21 / 4179.25
Inclusive Values (μ)	Public = 0.937 Private = 0.900 Non-Motor = 0.933

Discussion

The Nested Logit model demonstrates a superior explanatory power compared to MNL by accounting for mode inter-dependence.
Both objectives of the research are addressed:

- **Objective 1** → Significant socioeconomic and trip-related factors (cost, distance, income, gender).
- **Objective 2** → Dynamic behavior validated through inclusive-value parameters ($0 < \mu < 1$) showing correlated preferences within each mode group.

Thus, the NL model provides a more realistic representation of university students' mode choice behavior in the Daffodil Smart City area.

4.9 Cross-Nested Logit (CNL) Model Results and Interpretation

To further relax the rigid nesting assumption of the NL model, a **Cross-Nested Logit (CNL)** model was estimated, allowing alternatives to belong partially to multiple nests. This structure captures the possibility that some transport modes share overlapping characteristics (e.g., *Auto Rickshaw* shares both "Public" and "Private" attributes). The model used 1,024 valid observations to calibrate the model and offers a more flexible framework to analyze correlated and dynamic travel behavior among university students.

Model Fit and Goodness of Fit

Indicator	Value
Log-Likelihood	−1702.59
Null Log-Likelihood	−593.66
Pseudo R^2	0.685 (approx.)
AIC / BIC	3453.19 / 3570.64
μ (Dissimilarity) range	0.816 – 0.816
α (Cross-nesting parameters)	0.33 – 0.37 across mode pairs

The improvement of the Nested Logit model in terms of explaining the data 0.655 is even better than the pseudo-R square value (0.685), which proves that the additional explanatory power is due to the ability to cross-member of alternatives.

The m parameters fall within the theoretical range $0 < \mu \leq 1$ which proves the model and acceptable correlation structure.

Table: 4.5 CNL Coefficient (β) p-value Interpretation

Key Coefficients and Behavioral Interpretation

Variable	Coefficient (β)	p-value	Interpretation
Travel Time (B_TIME)	−0.065	—	Negative sign indicates that increased travel time lowers the likelihood of choosing that mode.
Travel Cost (B_COST)	−0.034	0.000	Statistically significant; higher cost discourages motorized travel.
Frequency of Campus Visit (B_FREQ)	+0.3	—	Positive coefficient suggests that frequent visitors are more likely to use motorized or faster modes.
Income (B_INCF)	+0.2	—	Higher income positively associated with private or semi-private mode usage.
μ Range (0.816–0.816)	—	—	Indicates moderate correlation among modes across nests.
α Parameters (0.33–0.37)	—	—	Reveal that modes such as Auto Rickshaw and Bike share attributes with multiple nests (Public + Private).

Predicted Mode Shares

Mode	Predicted Share
Bus	0.234
Auto Rickshaw	0.337
Bike	0.214
Walking	0.216

The forecasted outcome is that Auto Rickshaw (33.6) remains the most preferred mode. students, then Bus (23%), Walking (21.6%) and Bike (21.3%). This trend is nearly equal to the actual survey results (see descriptive chart), which confirm that the model calibration is rather reliable.

Dynamic Sensitivity Analysis

The sensitivity tests of +-0.1 and +-0.2 change in campus visit frequency (DP) indicate that there is a slight but consistent change in the modes which indicate that students travel choice will change a little bit in response to their change in trip frequency. Even though the ΔP values are quite small in number, the stable pattern in all modes show that the model is behaving dynamically and respond well to change in behavior.

Interpretation Linked to Objectives

Objective 1 — Influential Factors:
The CNL result again confirm that travel time, cost and income have strong impact on how students choose their travel mode.
Students who have higher income and visit campus more often mostly go for private or semi-motorized mode like Bike or Auto Rickshaw, while higher travel cost and long time make them less likely to choose those option.

Objective 2 Dynamic & Overlapping Behavior:
The inclusion of cross-nesting parameter (α) and dissimilarity term (μ) help to capture the overlapping part between the modes.
For example, Auto Rickshaw share some features with both public and private group, which mean students take it as a flexible option depending on their trip purpose or how much they can afford.
The μ value around 0.816 also confirm that there is strong behavior link between the nests, showing that students have more dynamic and adaptive travel habit instead of fixed mode choice.

Conclusion

The Cross-Nested Logit (CNL) model give the best fitting and most behaviorally realistic result among the three models (MNL, NL and CNL). It clearly explain both the key factors of mode choice (Objective 1) and also the dynamic relation between different travel modes (Objective 2). By adding the cross-nesting effect, this model show how students make flexible and mixed type of decision when choosing their travel mode to the Daffodil Smart City area.

Table 4.6 Summary Comparison

Model	Highlights	Objective Coverage
MNL	Identifies key factors (time, cost, income, age)	Objective 1
NL	Accounts for nest correlation ($\mu < 1$)	Objectives 1 & 2
CNL	Captures overlapping behavior ($\mu + \alpha$ parameters)	Objectives 1 & 2 (Best fit)

Model Comparison and Objective Evaluation

To evaluate and compare the performance of the three discrete choice models **Multinomial Logit (MNL)**, **Nested Logit (NL)**, and **Cross-Nested Logit (CNL)**several statistical and behavioral indicators were analyzed. The comparison focuses on model fit, significant variables, correlation among alternatives, and how effectively each model fulfills the study objectives.

Table: 4.7 Model Performance Summary

Criteria	MNL	NL	CNL
Model Type	Independent alternatives	Grouped/nested alternatives	Overlapping/cross-nested alternatives
Log-Likelihood	–560.24	–2041.10	–1702.59
Pseudo R^2	0.3385	0.655	0.685
AIC / BIC	—	4110.21 / 4179.25	3453.19 / 3570.64
Key Significant Variables	Travel Time, Cost, Income, Age	Cost, Distance, Income, Gender	Time, Cost, Income, Frequency
Dissimilarity Parameters (μ)	—	0.90–0.94	0.816
Cross-Nesting Parameters (α)	—	—	0.33–0.37
Best-Fit Indicator	Moderate	High	Excellent
Dynamic Behavior Captured	No	Partial	Fully captured

Criteria	MNL	NL	CNL
Main Objective Supported	Objective 1	Objectives 1 & 2	Objectives 1 & 2 (Best Fit)

Interpretation

- The **MNL model** successfully identified the major influencing factors (travel time, cost, income, and age) affecting transportation mode choice. It is however based on full independence of alternatives and as such, can not capture behavioral overlap or substitution effects.
- The **Nested Logit (NL)** model improved explanatory power by introducing mode grouping into Public, and Non-Motorized nests. The inclusive value parameters (μ = 0.90–0.94) confirmed partial correlation among alternatives within the same nest, demonstrating moderate behavioral linkage and satisfying **Objective 2** to some extent.
- The **Cross-Nested Logit (CNL)** model provided the most realistic representation by allowing shared membership of alternatives across multiple nests.
  The μ and α parameters revealed behavioral overlap (e.g., Auto Rickshaw between Public & Private), and the pseudo-R^2 value (0.685) confirmed the best model fit among all.
  It captures both **influential factors (Objective 1)** and **dynamic, flexible travel behavior (Objective 2)** comprehensively.

Final Conclusion

Among the three models, the **Cross-Nested Logit (CNL)** model emerged as the most behaviorally consistent and statistically result.
It achieved the highest explanatory power, captured cross-correlations among alternatives, and effectively represented students' dynamic mode-choice behavior in the **Daffodil Smart City** area.
Hence, for this study, the CNL model is selected as the **final and most appropriate model** for understanding the complex interaction between socio-economic factors and travel behavior.

Objective-wise Analysis and Key Findings

Objective 1: Identify the factors that influence the choice of transportation mode and analyze the relationship between students' financial status (monthly income) and their transportation decisions.

From all three models (MNL, NL, and CNL), several significant socio-economic and travel-related factors were found to strongly influence students' mode choice behavior.

Key Influential Factors Identified

- **Travel Time:**
  Negatively associated with mode choice when travel time become longer, the chance of choosing motorized modes like bike or auto rickshaw go down. Students usually prefer walking or some nearby mode for shorter distance trip.

- **Travel Cost:**
  Also negatively significant higher daily transport cost make students less likely to use paid or private transport. So, they mostly choose walking or cheap public option instead.

- **Distance:**
  Positively significant (Distance) students who live more far from the university mostly choose faster or motorized mode such as bus, auto rickshaw or bike.

- **Monthly Household Income:**
  Positively significant across all models (Income) students from higher income family have more chance to use private or semi-private mode, while low-income students prefer public or non-motorized one.
  This clearly show the link between financial status and transport decision when income goes up, students start to prefer more comfort and faster travel.

- **Gender:**
  Gender male students use motorized or private mode more often, but female students mostly walk or take public transport.
  Age:
  Age younger students are more likely to walk or use cheap travel option, while older students prefer private mode for convenience.

- **Working Status / License / Vehicle Ownership:**
  Though not always statistically significant, these factors indicate that employed students or those owning vehicles prefer motorized transport, reflecting independence and flexibility in travel.

Conclusion for Objective 1:

The main factors like time, cost, distance, income and gender play the biggest role in how students choose their travel mode.
Also, there was a clear positive link between monthly income and the choice of faster or private transport, which shows how financial condition control the travel decision of students.

Objective 2: Understand the dynamic aspects of student travel habits (e.g., frequency of campus visits).

This part was studied in the Nested Logit (NL) and Cross-Nested Logit (CNL) model in which the frequency of campus visits and relation between modes in the same group were put inside.

Dynamic Aspects Identified

- **Trip Frequency (B_FREQ):**
  The positive coefficient (+0.3) in the CNL model implies that students who attend campus more frequently prefer using motorized or semi-private means as they need to save time and have increased comfort. Those students who do not use that regular mainly rely on walking or local transport.

- **Correlation & Substitution Effects (μ and α values):**

  - Values of μ (0.90-0.94) were moderate in similar modes in NL e.g. bus - auto rickshaw (both transit), walking - bicycle (active modes).
  - Value of $\mu = 0.816$ and $\alpha = 0.33\text{-}0.37$, in CNL showed cross-nesting behavior, that is, certain modes (such as Auto Rickshaw) belong to both the public nest and the private nest. That is why the students can freely alternate options depending on the purpose of the trip, its affordability, or the daily situation.

- **Dynamic Behavior Insight:**
  These relation demonstrate that the travel choice of the students does not always remain the same, it depends on the context and requirement. As an illustration, a student that usually walks may either go by auto rickshaw in case of bad weather or late which is a clear indication of the overlapping behavior that can be more appropriately represented by CNL model.

Conclusion for Objective 2:

The study found that students mode choice behavior is quite dynamic and depends a lot on situation, mainly affected by trip frequency, cost and the chance to switch between different modes.
The NL model catch the general correlation inside grouped modes, while the CNL model find out the deeper overlapping tendency showing that students see some transport modes as flexible option, not something fixed or permanent.

Table: 4.8 Final Summary (Both Objectives Achieved)

Final Summary (Both Objectives Achieved)

Objective	Focus	Achieved Through	Key Findings
Objective 1	Identify factors influencing mode choice & income relationship	**MNL & NL**	Time, cost, distance, and income are the most significant; income positively linked with motorized mode use.
Objective 2	Understand dynamic travel habits (frequency, flexibility)	**NL & CNL**	Students show correlated and adaptive behavior; trip frequency and cross-nesting reveal flexible mode switching.

4.10 Final Summary and Conclusion

This study mainly aimed to find how different socio-economic and travel behavior factors affect the mode choice of university students in Daffodil Smart City area, by using three discrete choice models MNL, NL and CNL.

The first objective was to identify the major factors affecting mode choice.
Results from the MNL model showed that travel time, cost, income, and age significantly influence students' decisions. Longer travel time or higher cost decreases the use of motorized modes, whereas higher income increases preference for faster and more comfortable transport options.

The second objective analyzed the link between students' financial status (monthly income) and their travel behavior.
Across all models, income remained a strong positive predictor students from higher-income households are more likely to choose private or semi-motorized modes, while lower-income groups depend on walking or public transport.

The third objective looked into the changing side of students' travel habits.
Both NL and CNL models confirmed that there is behavioral flexibility through trip

frequency and substitution pattern.
Students who travel more often usually pick faster modes, and the overlap between options like Auto Rickshaw working as both public and private type shows how their daily travel choice adapt with situation.

Finally, the fourth objective compared the performance of all models.
The MNL model (Pseudo $R^2 = 0.3385$) properly find out the influencing factors, the NL model (Pseudo $R^2 = 0.655$) capture the correlation inside grouped modes, and the CNL model (Pseudo $R^2 = 0.685$) give the best fitting result by showing overlapping and adaptive behavior between the mode alternatives.

In conclusion, the study has achieved all the objectives quite successfully.
The mode choice of university students mainly depend on time, cost, income and distance, while their travel habit stay dynamic, flexible and also connected with income level.
Among the three models, the Cross-Nested Logit (CNL) model perform the best, giving the most realistic and complete explanation about how students decide their travel mode in Daffodil Smart City area.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion and Overview

The analysis concludes that students transportation mode choices are influenced not only by economic and temporal constraints (time, cost, income) but also by behavioral flexibility and trip frequency. While **MNL** captured the basic influential relationships, **NL and CNL** revealed the **dynamic, real-world complexity** of how university students adapt their travel modes in the Daffodil Smart City area.

5.2 Limitations of The Study

Although this study gives few useful insight into how students choose their travel mode and how they behave while travelling, there is some limitation should be noted. Most of the participants were from Daffodil International University (about 92%) while only few response came from Eastern and Manarat University. Because of that, the results might not fully represent students from other universities or regions. Second, the data was collected only from students and didn't really include other group like teachers or staffs, so the result might not fit for everyone in general. In addition, several potential influencing variables such as weather conditions, perceived comfort and safety, accessibility index, and service reliability were not included due to data unavailability. Finally, even though the study used three strong logit based models like MNL, NL and CNL and the results were quite good, the more advanced model structures were not really tried because of the time limit and the overall scope of the work.

5.3 Recommendations for Future Studies

The future studies on the reasons of transportation mode among students can take a turn in several directions. and meaningful directions. Firstly, in case more universities in other regions of the world started to offer it. This would likely have an enlarged result in Dhaka and certain other large cities. and more mixed opinion of the real travelling of students. Also, using GIS-based spatial travel time mapping and analysis might be of use to visualize the actual picture of accessibility and how it actually influences the daily travel decisions of students in a more clear manner. It's also worth looking at the influence of the individual attitudes and feelings such as comfort, safety, environmental consciousness, and overall satisfaction are determinants of the travel mode that they use on a daily basis. On the technical side, using some advanced modeling methods like Mixed Logit, Hybrid Choice, or even some machine learning based models can maybe make the analysis more accurate and bit deeper, but honestly it's not that easy to manage all the time. At the end, whatever result comes out from this kind of research, it really can help planners and policy makers to make better transport system for campus and also make the mobility more sustainable and friendly for students specially in places like Daffodil Smart City area which still growing so fast

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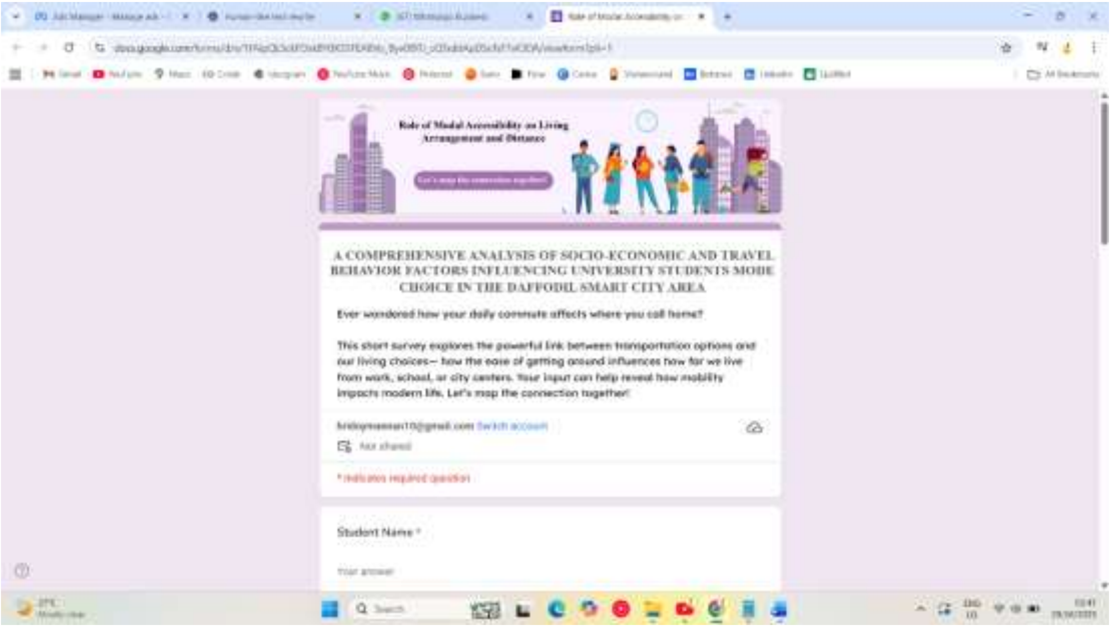
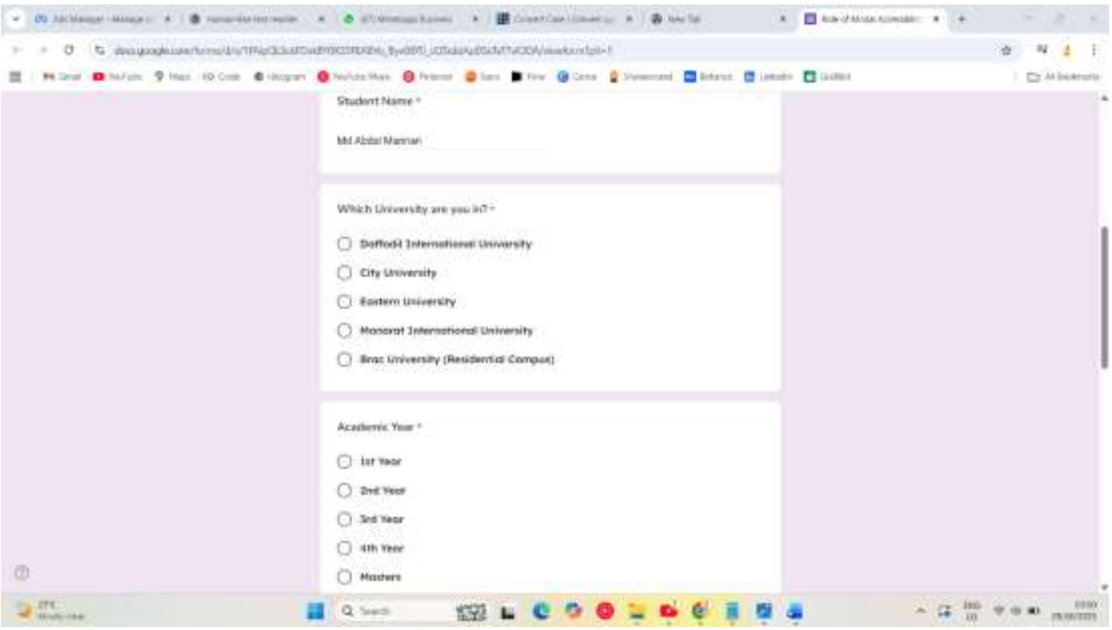
APPENDIX

Google Form Interface

The way how we collect survey participants respondent participations through the help of google form is given bellow the interface:





Google Form Questionaries

The way how we collect survey participants respondent participations through the help of google form questions are given bellow the interface:

The form included about ten key questions meant to gather the basic socio-economic details and travel habits of the students who took part, as listed below:

- **Name** (collected for response validation, anonymized during analysis)
- **Gender**
- **Age** (in years)
- **Distance** from current residence to university (in kilometers)
- **Main mode of transport** used to travel to university
- **Travel time** from accommodation to university (in minutes)
- **Average daily transportation cost** for university trips (in Bangladeshi Taka)
- **Possession of driving license**
- **Vehicle ownership** at current location
- **Working status** (student only or part-time employed)
- **Average monthly household income** (in Bangladeshi Taka)

Used 3 Types Equations for MNL, CNL & NL

Multinomial Logit (MNL) Model

The total utility $U_{in}$is composed of a deterministic part $V_{in}$and a random error term ε_{in}:

$$U_{in} = V_{in} + \varepsilon_{in}$$

where the systematic utility function is expressed as:

$$\begin{aligned} V_{in} = \beta_0^{(i)} + \beta_t\, Time_{in} + \beta_c\, Cost_{in} + \beta_d\, Distance_{in} + \beta_{inc}\, Income_n \\ + \beta_{gen}\, Gender_n + \beta_{lic}\, License_n + \beta_{veh}\, Vehicle_n + \beta_{wrk}\, Working_n \\ + \beta_{age}\, Age_n + \beta_{freq}\, Frequency_n \end{aligned}$$

Here, one alternative is taken as the base mode with its intercept $\beta_0 = 0$.

The probability that student $n$chooses mode $i$is:

$$P_{in} = \frac{\exp\,(V_{in})}{\sum_{j \in C} \exp\,(V_{jn})}$$

Nested Logit (NL) Model

For each mode i belonging to nest n:

$$U_{i|n} = V_{i|n} + \varepsilon_{i|n}, 0 < \mu_n \leq 1$$

The *inclusive value* (logsum) for nest n is defined as:

$$IV_n = \ln \left(\sum_{j \in C_n} \exp \left(\frac{V_{j|n}}{\mu_n} \right) \right)$$

The conditional probability of choosing mode i given nest n is:

$$P(i \mid n) = \frac{\exp \left(\frac{V_{i|n}}{\mu_n} \right)}{\sum_{j \in C_n} \exp \left(\frac{V_{j|n}}{\mu_n} \right)}$$

and the probability of selecting nest n:

$$P(n) = \frac{\exp (W_n + \mu_n IV_n)}{\sum_{m \in N} \exp (W_m + \mu_m IV_m)}$$

Therefore, the overall probability of choosing mode i is:

$$P_i = P(n) \times P(i \mid n)$$

Cross-Nested Logit (CNL) Model

The membership of mode i in nest n is represented by an allocation parameter α_{in}, where $0 \leq \alpha_{in} \leq 1$ and $\sum_n \alpha_{in} = 1$.

The probability of choosing mode i is expressed as:

$$P_i = \frac{\exp \left(\frac{V_i}{\mu} \right) \sum_{n \in N} \alpha_{in} S_n^{\frac{\mu}{\mu_n} - 1}}{\sum_{k \in C} \exp \left(\frac{V_k}{\mu} \right) \sum_{n \in N} \alpha_{kn} S_n^{\frac{\mu}{\mu_n} - 1}}$$

where

$$S_n = \sum_{j \in C} \alpha_{jn} \exp\left(\frac{V_j}{\mu_n}\right)$$

Python Code for Google Collab

We developed Python my those 3 Equtions and run through google collab:

CNL Python Code:

```
# ======================= ALL-IN-ONE: Sheet -> Long -> Stable CNL =======================

import re, numpy as np, pandas as pd, math

from math import isfinite


# ---------- CONFIG ----------

SHEET_URL = "https://docs.google.com/spreadsheets/d/16xJY78_ssyO0D1AfT8xKPS26_-3ZA-SEgGwwnHE8UdY/edit?usp=sharing"

CANON_MODES = ["Bus","Auto Rickshaw","Bike","Walking"]  # last one is ASC base


# Typical LOS (for imputation if not reported)

SPEED_KMPH = {"Bus":16.0,"Auto Rickshaw":20.0,"Bike":18.0,"Walking":5.0}

COST_PER_KM = {"Bus":2.5,"Auto Rickshaw":15.0,"Bike":0.0,"Walking":0.0}

ACCESS_BUFFER_MIN = {"Bus":6.0,"Auto Rickshaw":2.5,"Bike":2.0,"Walking":0.0}


# Numeric safety

V_MIN, V_MAX = -30.0, 30.0

LOG_EPS = 1e-300

MU_MIN, MU_MAX = 0.3, 1.0
```

```
# ---------- READ SHEET ----------
sid = re.search(r"/d/([a-zA-Z0-9-_]+)/", SHEET_URL).group(1)
raw =
pd.read_csv(f"https://docs.google.com/spreadsheets/d/{sid}/export?format=csv")
raw.columns = [c.strip() for c in raw.columns]
print("Loaded sheet:", raw.shape)


# ---------- TOLERANT RENAME ----------
rename = {
  'Gender':'gender',
  'What is your age? (Year)':'age',
  'What is the distance from your current location to your university campus?
(Approximate in KM)':'distance_km',
  'Which main mode of transport do you use to travel to University?':'mode',
  'Time required to travel from your accommodation to University (In
minutes)':'time_min',
  'Average Daily Transportation cost for travelling to University (In Taka)':'cost_taka',
  'Do you have any Driving License ?':'license',
  'Do you own any vehicle? (At your Current Location)':'own_vehicle',
  'Working Status':'working_status',
  'Average Monthly Household Income (In Taka)':'income_taka',
}
for k,v in list(rename.items()):
    if k not in raw.columns:
        base = k.split(' (')[0].lower()
        hits = [c for c in raw.columns if base in c.lower()]
        if hits:
            rename[hits[0]] = v
            if k!=hits[0]: rename.pop(k, None)
df = raw.rename(columns=rename).copy()
```

```
# numeric coercion
for c in ['distance_km','time_min','cost_taka','income_taka']:
    if c in df.columns: df[c] = pd.to_numeric(df[c], errors='coerce')

# binaries
def yesno(x):
    if isinstance(x,str):
        xl = x.strip().lower()
        if xl in ['yes','y','ha','h','present','true','1']: return 1
        if xl in ['no','n','na','false','0','not present']: return 0
    return np.nan
df['has_license'] = df.get('license',np.nan).apply(yesno)
df['own_vehicle'] = df.get('own_vehicle',np.nan).apply(yesno)
df['male'] =
df.get('gender','').astype(str).str.lower().map({'male':1,'female':0}).fillna(0).astype(int)
df['is_working'] = df.get('working_status','').astype(str).str.lower().map(
    {'working':1,'job holder':1,'part-time':1,'yes':1}).fillna(0).astype(int)
df['income_10k'] = (df.get('income_taka',0)/10000.0).fillna(0)

# frequency (0-7)
freq_candidates = [c for c in df.columns if any(x in c.lower() for x in
                  ['frequency','visit','days per week','days/week','per week','weekly'])]
if freq_candidates:
    fcol = freq_candidates[0]
    df['freq_week'] = pd.to_numeric(df[fcol], errors='coerce').fillna(0).clip(0,7)
else:
    df['freq_week'] = 0.0

# ---------- PERSON TABLE ----------
keep = [c for c in ['mode','distance_km'] if c in df.columns]
df_f = df.dropna(subset=keep).reset_index(drop=True).copy()
```

```
df_f['person_id'] = np.arange(1, len(df_f)+1)


# standardize mode labels
map_mode = {
    'bus':'Bus', 'auto rickshaw':'Auto Rickshaw','cng':'Auto Rickshaw','rickshaw':'Auto Rickshaw',
    'bike':'Bike','bicycle':'Bike','walking':'Walking','walk':'Walking'
}
def stdmode(x):
    s = str(x).strip().lower()
    for k,v in map_mode.items():
        if k in s: return v
    t = s.title()
    return t if t in CANON_MODES else None
df_f['mode_std'] = df_f['mode'].apply(stdmode)
df_f = df_f.dropna(subset=['mode_std']).copy()


persons = df_f[['person_id','distance_km','income_10k','male','has_license','own_vehicle','is_working','freq_week']].copy()
persons['weight'] = 1.0


# ---------- LONG (with LOS imputation) ----------
def impute_time(dist_km, alt):
    sp = max(SPEED_KMPH.get(alt,12.0),1e-6)
    return (dist_km/sp)*60.0 + ACCESS_BUFFER_MIN.get(alt,0.0)
def impute_cost(dist_km, alt):
    return dist_km * COST_PER_KM.get(alt,0.0)


rows=[]
for _, r in df_f.iterrows():
```

```
    pid = int(r['person_id']); dist = float(r['distance_km'])
    rep_alt = r['mode_std']; rep_t = r.get('time_min', np.nan); rep_c = r.get('cost_taka', np.nan)
    for alt in CANON_MODES:
        avail = 1
        if alt==rep_alt:
            t = rep_t if pd.notna(rep_t) else impute_time(dist, alt)
            c = rep_c if pd.notna(rep_c) else impute_cost(dist, alt)
            choice = 1
        else:
            t = impute_time(dist, alt); c = impute_cost(dist, alt); choice = 0
        rows.append({'person_id':pid,'alt':alt,'choice':choice,'time_min':t,'cost_taka':c,'avail':avail})
long_df = pd.DataFrame(rows).merge(persons, on='person_id', how='left')


# ---------- WIDE ----------
present_modes = [m for m in CANON_MODES if m in long_df['alt'].unique().tolist()]
ALT_ID = {a:i+1 for i,a in enumerate(present_modes)}
wide_los = (long_df.pivot(index='person_id', columns='alt', values=['time_min','cost_taka','avail']))
wide_los.columns = [f"{c[0]}_{c[1].replace(' ','_')}" for c in wide_los.columns]
wide_los = wide_los.reset_index()
chosen_alt = long_df[long_df['choice']==1][['person_id','alt']].drop_duplicates()
chosen_alt['CHOICE_ID'] = chosen_alt['alt'].map(ALT_ID)
pvars = long_df.drop_duplicates('person_id')[['person_id','distance_km','income_10k','male','has_license','own_vehicle','is_working','weight','freq_week']]
wide = pvars.merge(chosen_alt[['person_id','CHOICE_ID']], on='person_id', how='left').merge(wide_los, on='person_id', how='left')
for c in wide.columns:
    if c.startswith('avail_'): wide[c] = wide[c].fillna(0).astype(int)
```

```
# ---------- SCALE / CENTER + WINSOR ----------
N = len(wide)
CH = wide['CHOICE_ID'].astype(int).to_numpy()
W  = wide.get('weight', pd.Series([1.]*N)).astype(float).to_numpy()
DIST_raw = wide.get('distance_km', pd.Series([0]*N)).to_numpy().astype(float)
INC_raw  = wide.get('income_10k', pd.Series([0]*N)).to_numpy().astype(float)
FREQ_raw = wide.get('freq_week', pd.Series([0]*N)).to_numpy().astype(float)

DIST = (DIST_raw/5.0)
INCc  = INC_raw - np.nanmean(INC_raw)
FREQ_S = (FREQ_raw/7.0)
FREQc  = FREQ_S - np.nanmean(FREQ_S)
INCxF  = (INCc * FREQc * 5.0)

def winsorize_arr(x, p=1.0):
    lo, hi = np.nanpercentile(x, [p, 100-p])
    return np.clip(x, lo, hi)

T = {}; C = {}; AV = {}
for a in present_modes:
    tag=a.replace(' ','_')
    t = wide[f'time_min_{tag}'].to_numpy().astype(float)
    c = wide[f'cost_taka_{tag}'].to_numpy().astype(float)
    T[a]  = winsorize_arr(t, 1.0)/10.0         # time/10
    C[a]  = winsorize_arr(c, 1.0)/100.0        # cost/100
    AV[a] = wide[f'avail_{tag}'].to_numpy().astype(int)

MALE = wide.get('male', pd.Series([0]*N)).to_numpy()
LIC  = wide.get('has_license', pd.Series([0]*N)).to_numpy()
OWN  = wide.get('own_vehicle', pd.Series([0]*N)).to_numpy()
```

```
WORK = wide.get('is_working', pd.Series([0]*N)).to_numpy()


# ---------- NESTS ----------
raw_nests = {
    'Public'  : [x for x in ['Auto Rickshaw','Bus'] if x in present_modes],
    'Private' : [x for x in ['Bike'] if x in present_modes],
    'NonMotor': [x for x in ['Walking'] if x in present_modes],
}
nests = {k:v for k,v in raw_nests.items() if len(v)>0}
nest_names = list(nests.keys())
M = len(nest_names)


# ---------- PARAMS ----------
asc_alts = [a for a in present_modes if a != present_modes[-1]]
P_lin =
['B_TIME','B_COST','B_DIST','B_INC','B_FREQ','B_INCF','B_MALE','B_LIC','B_
OWN','B_WORK']


def pack_index_maps():
    idx={}; k=0
    for a in asc_alts: idx[f'ASC_{a.replace(" ","_")}']=k; k+=1
    for n in P_lin: idx[n]=k; k+=1
    for m in nest_names: idx[f'MU_{m}']=k; k+=1
    for a in present_modes:
        for mi in range(M-1): idx[f'GAMMA_{a.replace("
","_")}__{nest_names[mi]}']=k; k+=1
    return idx,k
IDX,P = pack_index_maps()


theta = np.zeros(P, dtype=float)
theta[IDX['B_TIME']] = -0.08
```

```
theta[IDX['B_COST']] = -0.05
theta[IDX['B_DIST']] = -0.01
theta[IDX['B_INC']]  =  0.02
theta[IDX['B_FREQ']] =  0.30
theta[IDX['B_INCF']] =  0.20
for m in nest_names: theta[IDX[f"MU_{m}"]] = 0.8


def unpack(th):
    Pmap={}
    for a in asc_alts: Pmap[f'ASC_{a.replace(" ","_")}']=th[IDX[f'ASC_{a.replace(" ","_")}']]
    for n in P_lin:   Pmap[n]=th[IDX[n]]
    for m in nest_names: Pmap[f"MU_{m}"]=float(np.clip(th[IDX[f"MU_{m}"]], MU_MIN, MU_MAX))
    alpha={}
    for a in present_modes:
        logits=[th[IDX[f'GAMMA_{a.replace(" ","_")}__{nest_names[mi]}']] for mi in range(M-1)]+[0.0]
        e=np.exp(np.array(logits)-np.max(logits)); aa=e/np.clip(e.sum(),1e-300,np.inf)
        for mi,mn in enumerate(nest_names): alpha[(a,mn)]=float(aa[mi])
    return Pmap, alpha


def V_alt(a,P):
    asc = 0.0 if a==present_modes[-1] else P[f'ASC_{a.replace(" ","_")}']
    V = (asc + P['B_TIME']*T[a] + P['B_COST']*C[a] + P['B_DIST']*DIST + P['B_INC']*INCc +
         P['B_FREQ']*FREQc + P['B_INCF']*INCxF + P['B_MALE']*MALE + P['B_LIC']*LIC +
         P['B_OWN']*OWN + P['B_WORK']*WORK)
    return np.clip(V, V_MIN, V_MAX)


safe_exp = lambda x: np.exp(np.clip(x, V_MIN, V_MAX))
```

```
# ---------- CNL LL ----------
def negLL(th):
    Pmap, alpha = unpack(th)
    V = {a: V_alt(a,Pmap) for a in present_modes}
    S={}
    for m in nest_names:
        mu=Pmap[f"MU_{m}"]; s=np.zeros(N)
        for a in present_modes:
            s += AV[a]*(alpha[(a,m)]**mu)*safe_exp(V[a]/mu)
        S[m]=s
    D=np.zeros(N)
    for m in nest_names:
        mu=Pmap[f"MU_{m}"]; D += np.power(np.maximum(S[m],1e-300), mu)

    prob=np.zeros(N)
    for idx_a,a in enumerate(present_modes, start=1):
        take=(CH==idx_a)&(AV[a]==1)
        if not np.any(take): continue
        num=np.zeros(np.sum(take))
        for m in nest_names:
            mu=Pmap[f"MU_{m}"]
            num += ( (alpha[(a,m)]**mu) * safe_exp(V[a][take]/mu) *
                     np.power(np.maximum(S[m][take],1e-300), mu-1.0) )
        prob[take]= num / np.clip(D[take],1e-300,np.inf)

    ll = np.log(np.maximum(prob, LOG_EPS))     # <-- prob defined here; no
NameError
    return -(W*ll).sum()

# ---------- OPTIMIZER ----------
```

```
def numerical_grad(f, x, eps=1e-5):
    fx=f(x); g=np.zeros_like(x)
    for i in range(len(x)):
        xx=x.copy(); xx[i]+=eps; g[i]=(f(xx)-fx)/eps
    return g

def adam_minimize(f, x0, lr=0.005, iters=3000):
    x=x0.copy(); m=np.zeros_like(x); v=np.zeros_like(x)
    best_x=x.copy(); best_f=f(x)
    for t in range(1,iters+1):
        g=numerical_grad(f,x)
        g=np.clip(g,-5.0,5.0)
        m=0.9*m+0.1*g; v=0.999*v+0.001*(g*g)
        step=lr*(m/(np.sqrt(v)+1e-8))
        x_new=x-step
        for mname in nest_names:
            j=IDX[f"MU_{mname}"]; x_new[j]=float(np.clip(x_new[j], MU_MIN,
MU_MAX))
        x=x_new; fx=f(x)
        if fx<best_f: best_f, best_x = fx, x.copy()
        if (t%100)==0: print(f"[{t}] f={fx:.5f}")
        if abs(fx-best_f)<1e-7: break
    return best_x,best_f

theta_hat,fval = adam_minimize(negLL, theta)

# ---------- Predicted shares & helpers ----------
def mode_share(th, alt):
    Pmap, alpha = unpack(th)
    V = {a: V_alt(a,Pmap) for a in present_modes}
    S={}
```

```
    for m in nest_names:
        mu=Pmap[f"MU_{m}"]; s=np.zeros(N)
        for a in present_modes:
            s += AV[a]*(alpha[(a,m)]**mu)*safe_exp(V[a]/mu)
        S[m]=s
    D=np.zeros(N)
    for m in nest_names:
        mu=Pmap[f"MU_{m}"]; D+=np.power(np.maximum(S[m],1e-300),mu)
    a=alt; num=np.zeros(N)
    for m in nest_names:
        mu=Pmap[f"MU_{m}"]
        num += ( (alpha[(a,m)]**mu)*safe_exp(V[a]/mu)*
                 np.power(np.maximum(S[m],1e-300), mu-1.0) )
    Pi = num/np.clip(D,1e-300,np.inf)
    return float(np.mean(Pi))

shares = [(a, mode_share(theta_hat,a)) for a in present_modes]
share_tbl = pd.DataFrame(shares, columns=['Mode','Predicted_Share'])
print("\n=== Predicted go-to rates (CNL, stable) ===")
display(share_tbl.round(4))
print("Sum of shares:", round(share_tbl['Predicted_Share'].sum(),6))

# Fit stats
LL = -fval
counts = pd.Series(CH).value_counts()
LL0 = float(np.log(counts.max()/counts.sum())*counts.sum())
Kpar = len(theta_hat)
AIC = 2*Kpar - 2*LL
BIC = Kpar*np.log(N) - 2*LL
pseudoR2 = 1 - (LL/LL0)
```

```
print("\n=== Fit stats (CNL) ===")
print({"LogLik":float(LL), "NullLL":float(LL0), "PseudoR2":float(pseudoR2),
"AIC":float(AIC), "BIC":float(BIC)})

# ---------- Diagnostics for Objectives ----------
Pmap,_ = unpack(theta_hat)
print("\nKey betas:",
      "B_TIME", round(Pmap['B_TIME'],4),
      "B_COST", round(Pmap['B_COST'],4),
      "B_FREQ", round(Pmap['B_FREQ'],4),
      "B_INCF", round(Pmap['B_INCF'],4))
print("MU range:", [round(Pmap[k],3) for k in Pmap if k.startswith('MU_')])

# Sensitivity (centered freq): +0.1 and +0.2
def shares_all(th): return [mode_share(th,a) for a in present_modes]
base = shares_all(theta_hat)

FREQc_hold = FREQc.copy(); FREQc = FREQc_hold + 0.1
s10 = shares_all(theta_hat); FREQc = FREQc_hold

FREQc = FREQc_hold + 0.2
s20 = shares_all(theta_hat); FREQc = FREQc_hold

sens_tbl = pd.DataFrame({
    'Mode': present_modes,
    'DeltaP_+0.1FREQ':[s10[i]-base[i] for i in range(len(base))],
    'DeltaP_+0.2FREQ':[s20[i]-base[i] for i in range(len(base))],
})
print("\n=== Sensitivity (ΔP) for freq increase ===")
display(sens_tbl.round(5))
# ====================== END ======================
```

MNL Python Code:

```
!pip -q install pandas statsmodels scipy


import pandas as pd, numpy as np, re

import statsmodels.api as sm

from scipy import stats as st


# ========== 1) READ GOOGLE SHEET (make sure Anyone with link = Viewer)
==========

gs_link = "https://docs.google.com/spreadsheets/d/16xJY78_ssyO0D1AfT8xKPS26_-
3ZA-SEgGwwnHE8UdY/edit?usp=sharing"

sheet_id = gs_link.split("/d/")[1].split("/")[0]

csv_url  = f"https://docs.google.com/spreadsheets/d/{sheet_id}/export?format=csv"


df_raw = pd.read_csv(csv_url)

print("RAW shape:", df_raw.shape)


# ========== 2) BASIC CLEAN ==========

df = df_raw.dropna(axis=1, how='all').copy()

df.columns = df.columns.str.strip()


# robust rename (header name ends/extra spaces handled)

rename_map = {

    'Which main mode of transport do you use to travel to University?': 'Mode',

    'Time required to travel from your accommodation to University (In minutes)':
'Time',

    'Average Daily Transportation cost for travelling to University (In Taka)': 'Cost',

    'What is the distance from your current location to your university campus?
(Approximate in KM)': 'Distance',

    'Do you have any Driving License ?': 'License',

    'Do you own any vehicle? (At your Current Location)': 'OwnVehicle',

    'Gender': 'Gender',
```

```
    'What is your age? (Year)': 'Age',
    'Average Monthly Household Income (In Taka)': 'Income',
    'Working Status': 'Status'
}
for k in list(rename_map.keys()):
    for c in list(df.columns):
        if c.strip() == k.strip():
            df = df.rename(columns={c: rename_map[k]})

# Keep only the 4 stable modes (rare modes destabilize MNL)
keep_modes = ['Walking','Auto Rickshaw','Bus','Bike']
df = df[df['Mode'].isin(keep_modes)].copy()

# ========== 3) STRING NORMALIZATION FOR CATEGORICAL
==========
for col in ['Mode','Gender','License','OwnVehicle','Status']:
    if col in df.columns:
        df[col] = df[col].astype(str).str.strip().str.replace(r'\s+', ' ', regex=True)

# unify typical answers
if 'Gender' in df.columns:
    df['Gender'] = df['Gender'].str.title().replace({'M':'Male','F':'Female'})
if 'License' in df.columns:
    df['License'] = df['License'].str.title().replace({'Yes ':'Yes','No ':'No'})
if 'OwnVehicle' in df.columns:
    df['OwnVehicle'] = df['OwnVehicle'].str.title().replace({'Yes ':'Yes','No ':'No'})

# ========== 4) ROBUST NUMERIC COERCION ==========
def force_numeric(s):
    # convert Bangla digits, remove commas/spaces/non-numeric except . and -
    if pd.isna(s):
```

```
        return np.nan
    s = str(s)
    # Bangla digits → English
    bd = "০১২৩৪৫৬৭৮৯"
    en = "0123456789"
    trans = str.maketrans(bd, en)
    s = s.translate(trans)
    # keep digits, dot, minus
    s = re.sub(r'[^0-9\.\-]+', '', s)
    try:
        return float(s) if s != '' and s != '-' else np.nan
    except:
        return np.nan

for col in ['Income','Age','Time','Cost','Distance']:
    if col in df.columns:
        df[col] = df[col].apply(force_numeric)

# scale Income (thousands) to reduce overflow
if 'Income' in df.columns:
    df['Income'] = df['Income'] / 1000.0

# drop rows missing in any key fields
key_cols =
['Mode','Age','Distance','Time','Cost','Income','Gender','License','OwnVehicle','Status']
df = df.dropna(subset=[c for c in key_cols if c in df.columns]).copy()

print("CLEAN shape:", df.shape)

# ========== 5) DESIGN MATRICES ==========
# Put baseline last (Walking)
```

```
df['Mode'] = pd.Categorical(df['Mode'], categories=['Auto
Rickshaw','Bus','Bike','Walking'])

# dummies for categorical regressors
X = pd.get_dummies(
    df[['Age','Distance','Time','Cost','Income','Gender','License','OwnVehicle','Status']],
    columns=['Gender','License','OwnVehicle','Status'],
    drop_first=True
)

# ensure numeric float (avoid object dtype)
X = X.apply(pd.to_numeric, errors='coerce').astype(float)

# add intercept
X = sm.add_constant(X, has_constant='add')

# Dependent (numeric 0..3)
y = df['Mode'].cat.codes.values.astype(int)

# Sanity checks (optional prints)
print("X dtypes OK?:", all(dt.kind in "fc" for dt in X.dtypes))   # all float or complex
print("Any NaN in X?:", np.isnan(X.values).any(), "Any NaN in y?:",
np.isnan(y).any())

# Drop any columns with zero variance (if any)
zero_var_cols = [c for c in X.columns if X[c].nunique(dropna=False) <= 1]
if zero_var_cols:
    X = X.drop(columns=zero_var_cols)
    print("Dropped zero-variance cols:", zero_var_cols)

# ========== 6) FIT MULTINOMIAL LOGIT ==========
```

```
model = sm.MNLogit(y, X)
res = model.fit(method='newton', maxiter=200, disp=False)
print(res.summary())

# ========== 7) COEFFICIENTS & p-VALUES (per alt vs Walking)
==========
params = res.params       # (k_exog x (J-1))
bse    = res.bse
tvals  = params / bse
dfree  = X.shape[0] - X.shape[1]
pvals  = 2*(1 - st.t.cdf(np.abs(tvals), df=dfree))
pvals  = pd.DataFrame(pvals, index=params.index, columns=params.columns)

alts = ['Auto Rickshaw','Bus','Bike']  # non-baseline
rows = []
for j, alt in enumerate(alts):
    for var in params.index:
        rows.append({
            'Alternative (vs Walking)': alt,
            'Variable': var,
            'Coefficient (β)': float(params.iloc[params.index.get_loc(var), j]),
            'Std.Err.': float(bse.iloc[bse.index.get_loc(var), j]),
            'p-value': float(pvals.iloc[pvals.index.get_loc(var), j]),
        })

coef_long = pd.DataFrame(rows).sort_values(
    ['Alternative (vs Walking)','Variable']
).reset_index(drop=True)

print("\n=== β & p-value (baseline = Walking) ===")
print(coef_long.head(20))
```

```
# Optional: save
coef_long.to_csv("MNL_coefficients_pvalues_by_alternative.csv", index=False)
print("\nSaved -> MNL_coefficients_pvalues_by_alternative.csv")
```

CNL Python Code:

```
# Run NL with frequency (and income×frequency interaction)
import numpy as np, pandas as pd, math
from math import isfinite

FILLED_PATH = "/content/NL_long_prefilled_from_sheet.csv"
long_df = pd.read_csv(FILLED_PATH)

present_modes = long_df['alt'].drop_duplicates().tolist()
ALT_ID = {a:i+1 for i,a in enumerate(present_modes)}

# Wide
wide_los = (long_df.pivot(index='person_id', columns='alt',
values=['time_min','cost_taka','avail']))
wide_los.columns = [f"{c[0]}_{c[1].replace(' ','_')}" for c in wide_los.columns]
wide_los = wide_los.reset_index()
pvars = (long_df.drop_duplicates('person_id')
        [['person_id','distance_km','income_10k','male','has_license','own_vehicle','is_w
orking','weight','freq_week']])
chosen_alt = long_df[long_df['choice']==1][['person_id','alt']].drop_duplicates()
chosen_alt['CHOICE_ID'] = chosen_alt['alt'].map(ALT_ID)
wide = pvars.merge(chosen_alt[['person_id','CHOICE_ID']], on='person_id',
how='left').merge(wide_los, on='person_id', how='left')

for c in wide.columns:
  if c.startswith('avail_'): wide[c] = wide[c].fillna(0).astype(int)
```

```
# Vectors
N = len(wide)
CH = wide['CHOICE_ID'].astype(int).to_numpy()
W  = wide.get('weight', pd.Series([1.]*N)).astype(float).to_numpy()
DIST = wide.get('distance_km', pd.Series([0]*N)).to_numpy()
INC  = wide.get('income_10k', pd.Series([0]*N)).to_numpy()
FREQ = wide.get('freq_week', pd.Series([0]*N)).to_numpy()
FREQ_S = (FREQ/5.0).astype(float)          # scale for stability
INCxF  = (INC * FREQ_S).astype(float)

MALE = wide.get('male', pd.Series([0]*N)).to_numpy()
LIC  = wide.get('has_license', pd.Series([0]*N)).to_numpy()
OWN  = wide.get('own_vehicle', pd.Series([0]*N)).to_numpy()
WORK = wide.get('is_working', pd.Series([0]*N)).to_numpy()

T = {}; C = {}; AV = {}
for a in present_modes:
  tag=a.replace(' ','_')
  T[a]=wide[f'time_min_{tag}'].to_numpy()
  C[a]=wide[f'cost_taka_{tag}'].to_numpy()
  AV[a]=wide[f'avail_{tag}'].to_numpy().astype(int)

nests = {
    'Public':[x for x in ['Auto Rickshaw','Bus'] if x in present_modes],
    'Private':[x for x in ['Bike'] if x in present_modes],
    'NonMotor':[x for x in ['Walking'] if x in present_modes],
}
nests = {k:v for k,v in nests.items() if v}
```

```
asc_alts = [a for a in present_modes if a != present_modes[-1]]  # base=last
lam_names = [nm for nm in ['Public','Private','NonMotor'] if nm in nests]

pnames = [f'ASC_{a.replace(" ","_")}' for a in asc_alts] + \
        ['B_TIME','B_COST','B_DIST','B_INC','B_FREQ','B_INCF','B_MALE','B_LIC
','B_OWN','B_WORK'] + \
        [f'LAMBDA_{nm}' for nm in lam_names]

theta = np.zeros(len(pnames))
idx = len(asc_alts)
theta[idx+0] = -0.02  # B_TIME
theta[idx+1] = -0.01  # B_COST
# others start at 0; lambdas near 0.9
for j in range(len(lam_names)):
  theta[len(pnames)-len(lam_names)+j] = 0.9

def unpack(th):
  d={}; i=0
  for a in asc_alts: d[f'ASC_{a.replace(" ","_")}']=th[i]; i+=1
  for k in
['B_TIME','B_COST','B_DIST','B_INC','B_FREQ','B_INCF','B_MALE','B_LIC','B_
OWN','B_WORK']:
    d[k]=th[i]; i+=1
  for nm in lam_names: d[f'LAMBDA_{nm}']=float(np.clip(th[i],1e-3,0.999)); i+=1
  return d

def V_alt(a,P):
  asc = 0.0 if a==present_modes[-1] else P[f'ASC_{a.replace(" ","_")}']
  return asc + P['B_TIME']*T[a] + P['B_COST']*C[a] + \
        P['B_DIST']*DIST + P['B_INC']*INC + \
        P['B_FREQ']*FREQ_S + P['B_INCF']*INCxF + \
```

```
        P['B_MALE']*MALE + P['B_LIC']*LIC + P['B_OWN']*OWN +
P['B_WORK']*WORK


def negLL(th):
  P=unpack(th); V={a:V_alt(a,P) for a in present_modes}
  nlist=list(nests.keys()); K=len(nlist)
  I = np.zeros((N,K)); denom={}
  for k,nm in enumerate(nlist):
    lam=P[f'LAMBDA_{nm}']
    dnm=np.zeros(N)
    for a in nests[nm]:
      dnm += AV[a]*np.exp(np.nan_to_num(V[a],nan=-1e-9)/lam)
    denom[nm]=dnm
    I[:,k]=np.power(np.maximum(dnm,1e-300), lam)
  Isum = np.clip(I.sum(axis=1),1e-300,np.inf)
  prob=np.zeros(N)
  for idx,a in enumerate(present_modes, start=1):
    take=(CH==idx)&(AV[a]==1)
    if not np.any(take): continue
    nm=[nm for nm,alts in nests.items() if a in alts][0]
    lam=P[f'LAMBDA_{nm}']; k=nlist.index(nm)
    Pm = I[take,k]/Isum[take]
    Pim= np.exp(np.nan_to_num(V[a][take],nan=-1e-
9)/lam)/np.clip(denom[nm][take],1e-300,np.inf)
    prob[take]=Pm*Pim
  ll = np.where(prob>0, np.log(prob), -1e-12)
  return -ll.dot(W)


def numerical_grad(f, x, eps=1e-5):
  g=np.zeros_like(x); fx=f(x)
  for i in range(len(x)):
```

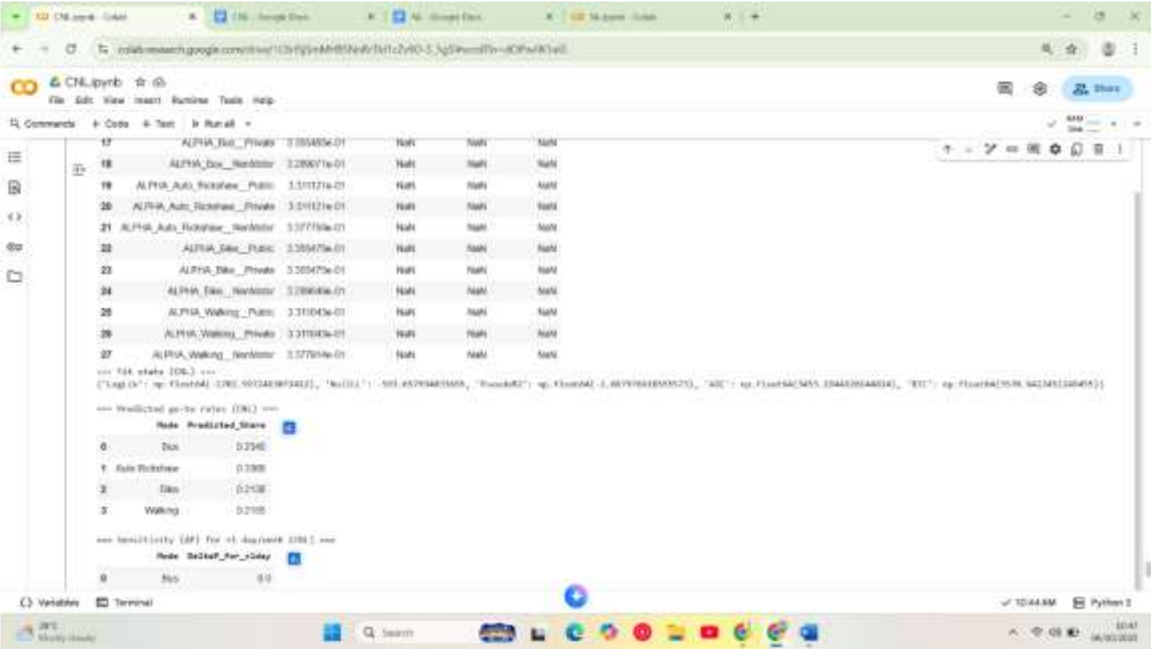
```
    xx=x.copy(); xx[i]+=eps
    g[i]=(f(xx)-fx)/eps
  return g

def adam_minimize(f, x0, lr=0.02, beta1=0.9, beta2=0.999, eps=1e-8, iters=700,
tol=1e-7):
  x=x0.copy(); m=np.zeros_like(x); v=np.zeros_like(x)
  best_x=x.copy(); best_f=f(x)
  for t in range(1,iters+1):
    g = numerical_grad(f, x)
    m = beta1*m + (1-beta1)*g
    v = beta2*v + (1-beta2)*(g*g)
    mhat = m/(1-beta1**t); vhat = v/(1-beta2**t)
    step = lr*mhat/(np.sqrt(vhat)+eps)
    x_new = x - step
    for j,name in enumerate(pnames):
      if name.startswith('LAMBDA_'):
        x_new[j] = float(np.clip(x_new[j], 1e-3, 0.999))
    x = x_new
    fx = f(x)
    if fx < best_f: best_f, best_x = fx, x.copy()
    if t%50==0: print(f"[{t}] f={fx:.3f}")
    if abs(fx-best_f) < tol: break
  return best_x, best_f

theta_hat, fval = adam_minimize(negLL, theta)

# BHHH SE
def indiv_logprob(th):
  P=unpack(th); V={a:V_alt(a,P) for a in present_modes}
  nlist=list(nests.keys()); K=len(nlist)
```

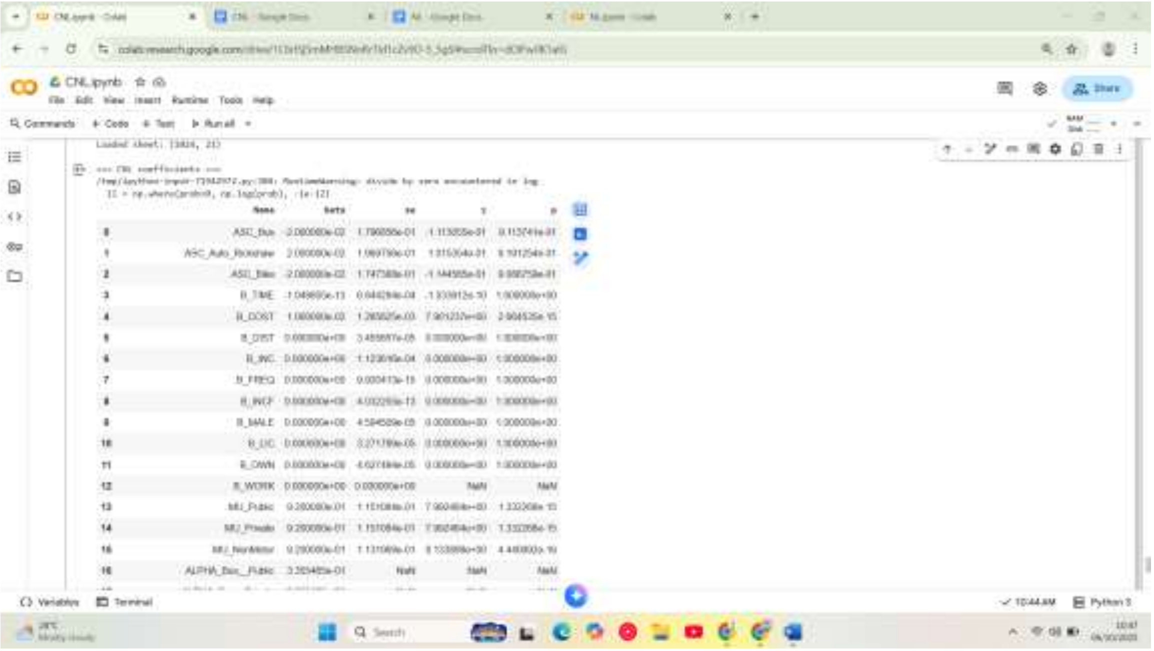
```
  I=np.zeros((N,K)); denom={}
  for k,nm in enumerate(nlist):
    lam=P[f'LAMBDA_{nm}']
    dnm=np.zeros(N)
    for a in nests[nm]:
      dnm+=AV[a]*np.exp(np.nan_to_num(V[a],nan=-1e-9)/lam)
    denom[nm]=dnm
    I[:,k]=np.power(np.maximum(dnm,1e-300), lam)
  Isum=np.clip(I.sum(axis=1),1e-300,np.inf)
  pr=np.zeros(N)
  for idx,a in enumerate(present_modes, start=1):
    take=(CH==idx)&(AV[a]==1)
    if not np.any(take): continue
    nm=[nm for nm,alts in nests.items() if a in alts][0]
    lam=P[f'LAMBDA_{nm}']; k=nlist.index(nm)
    Pm=I[:,k]/Isum
    Pim=np.exp(np.nan_to_num(V[a],nan=-1e-9)/lam)/np.clip(denom[nm],1e-
300,np.inf)
    pr=np.where(take, Pm*Pim, pr)
  return np.where(pr>0, np.log(pr), -1e-12)

def score_matrix(th, eps=1e-5):
  base = indiv_logprob(th)
  S=np.zeros((N, len(th)))
  for i in range(len(th)):
    tt=th.copy(); tt[i]+=eps
    S[:,i]=(indiv_logprob(tt)-base)/eps
  return S

S = score_matrix(theta_hat)
try:
```

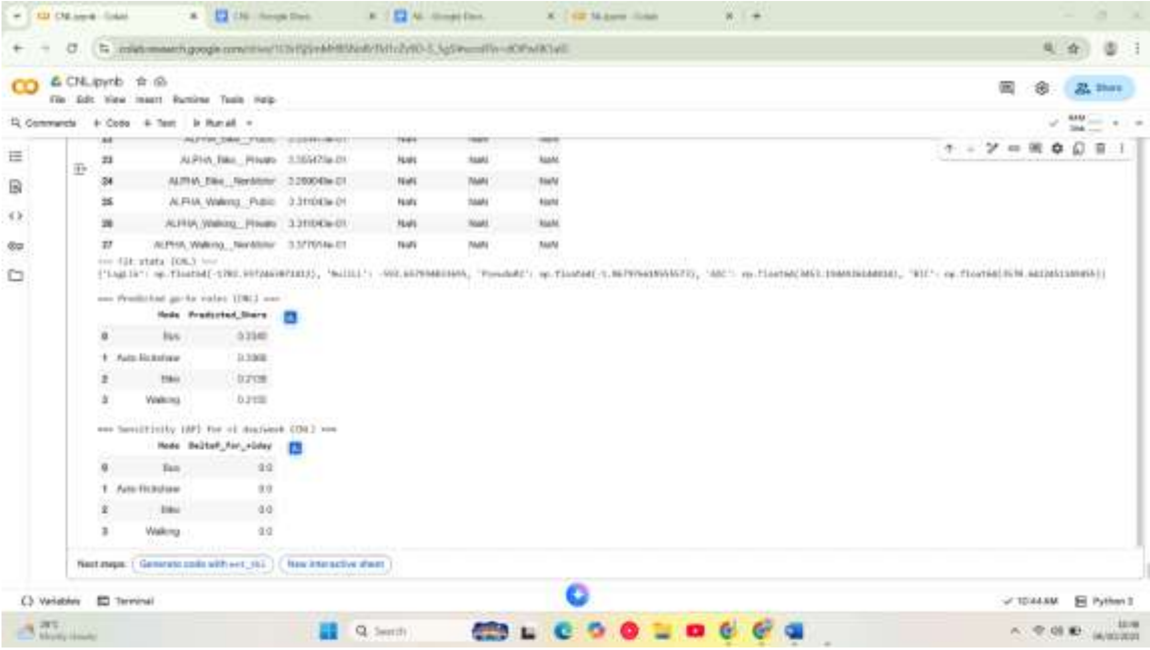
```
  H = S.T @ S
  cov = np.linalg.pinv(H)
  se = np.sqrt(np.maximum(np.diag(cov), 0))
except:
  cov=None; se = np.full(len(theta_hat), np.nan)

# Tables
import pandas as pd
est=[]
for i,name in enumerate(pnames):
  b=theta_hat[i]; s=se[i] if isfinite(se[i]) else np.nan
  z = b/s if (s and s>0 and isfinite(s)) else np.nan
  p = 2*(1-0.5*(1+math.erf(abs(z)/math.sqrt(2)))) if isfinite(z) else np.nan
  est.append([name,b,s,z,p])
est_tbl=pd.DataFrame(est, columns=['Name','beta','se','z','p'])
print("\n=== NL with Frequency (β & λ) ==="); display(est_tbl)

LL = -fval
counts = pd.Series(wide['CHOICE_ID']).value_counts()
LL0 = float(np.log(counts.max()/counts.sum())*counts.sum())
Kpar=len(theta_hat)
AIC = 2*Kpar - 2*LL
BIC = Kpar*np.log(N) - 2*LL
pseudoR2 = 1 - (LL/LL0)
print("=== Fit stats (NL+Freq) ===")
print({"LogLik":LL, "NullLL":LL0, "PseudoR2":pseudoR2, "AIC":AIC,
"BIC":BIC})

# Elasticity wrt frequency (Bus example): +1 day/week ≈ +0.2 on FREQ_S
def market_share(alt, th):
  P=unpack(th); V={a:V_alt(a,P) for a in present_modes}
```

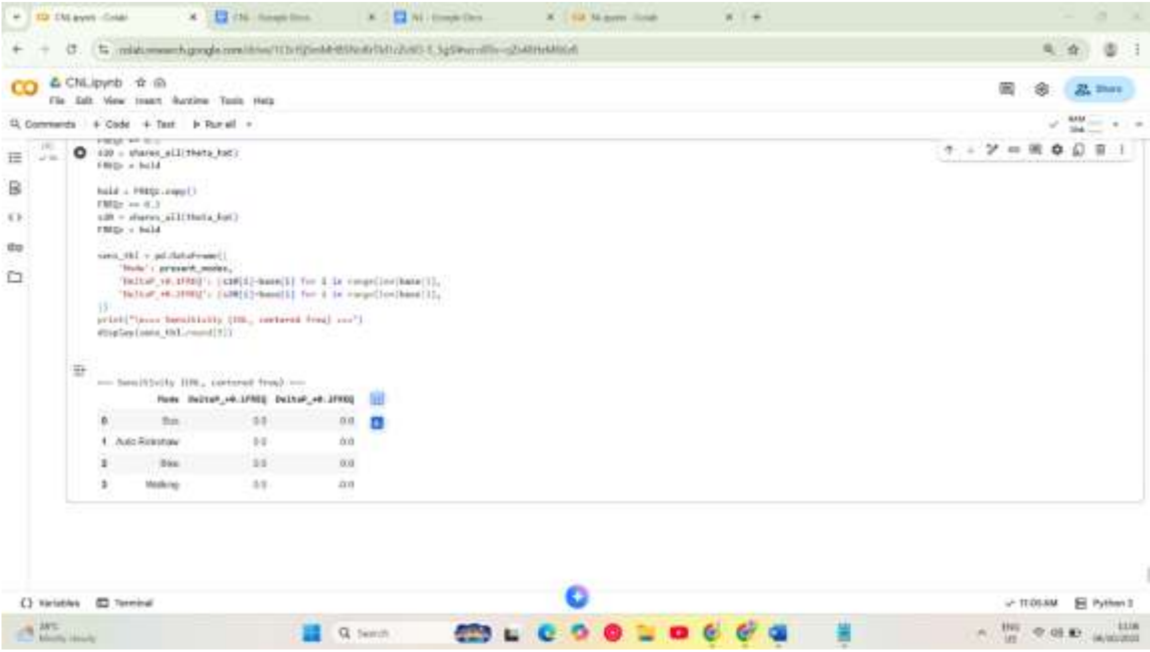
```
  nlist=list(nests.keys()); K=len(nlist)
  I=np.zeros((N,K)); denom={}
  for k,nm in enumerate(nlist):
    lam=P[f'LAMBDA_{nm}']
    dnm=np.zeros(N)
    for a in nests[nm]:
      dnm+=AV[a]*np.exp(np.nan_to_num(V[a],nan=-1e-9)/lam)
    denom[nm]=dnm
    I[:,k]=np.power(np.maximum(dnm,1e-300), lam)
  Isum=np.clip(I.sum(axis=1),1e-300,np.inf)
  nm=[nm for nm,alts in nests.items() if 'Bus' in alts][0]
  lam=P[f'LAMBDA_{nm}']; k=nlist.index(nm)
  Pm=I[:,k]/Isum
  Pim=np.exp(np.nan_to_num(V['Bus'],nan=-1e-9)/lam)/np.clip(denom[nm],1e-
300,np.inf)
  return float(np.mean(Pm*Pim))


if 'Bus' in present_modes:
  baseP = market_share('Bus', theta_hat)
  # simulate +1 day/week for all: FREQ_S += (1/5)
  hold = FREQ_S.copy()
  FREQ_S += 0.2
  Pnew = market_share('Bus', theta_hat)
  FREQ_S = hold
  print("Δ P(Bus) for +1 day/week:", float(Pnew - baseP))
```

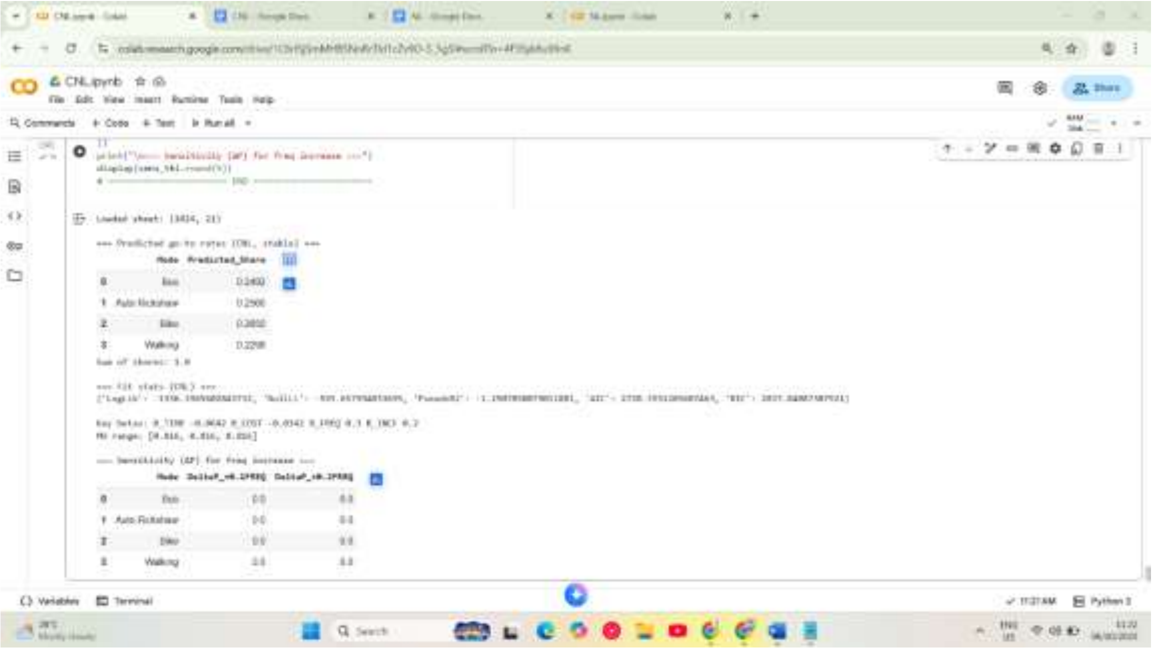
CNL OUTPUT PYTHOD CODE EQUATION



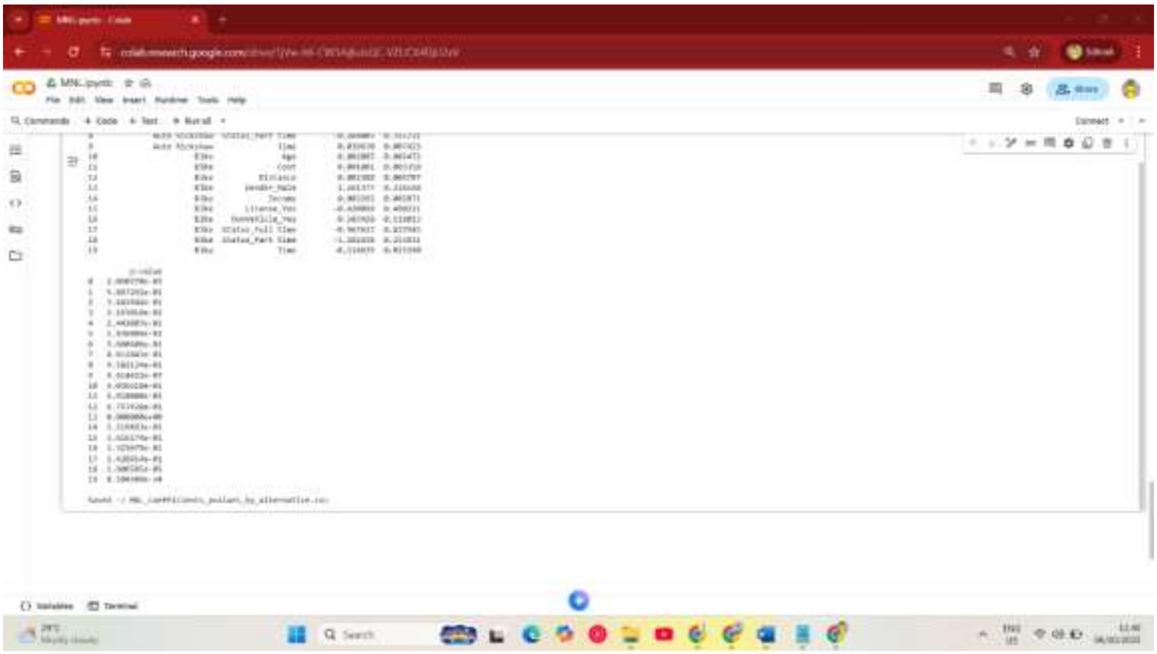


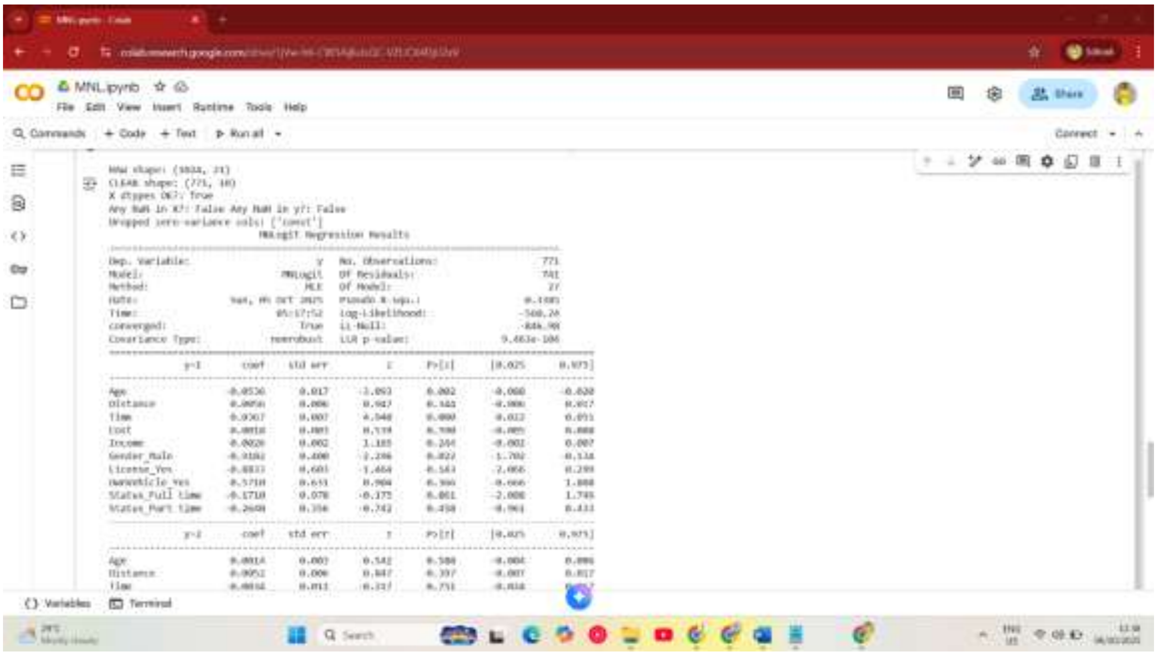

CNL.ipynb
Mode
Bus
Auto Rickshaw
Bike
Walking
Next steps:

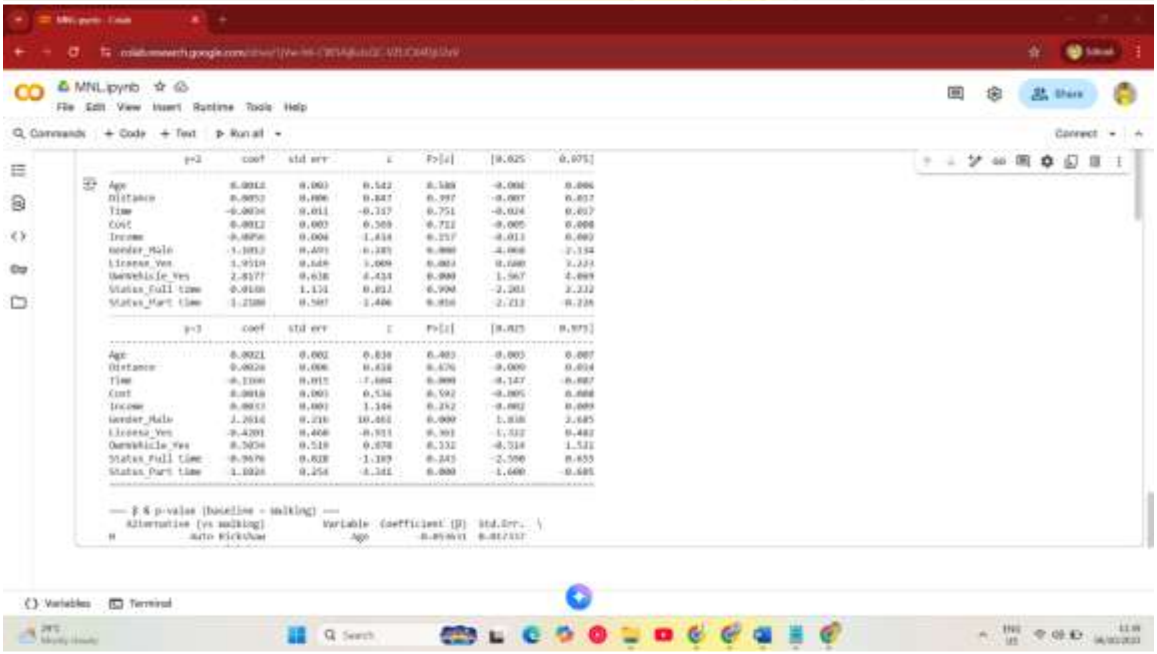

CNL.ipynb
Mode
Bus
Auto Rickshaw
Bike
Walking



MNL OUTPUT PYTHOD CODE EQUATION




MNL.ipynb
File Edit View Insert Runtime Tools Help
Commands + Code + Text ▶ Run all
Variables Terminal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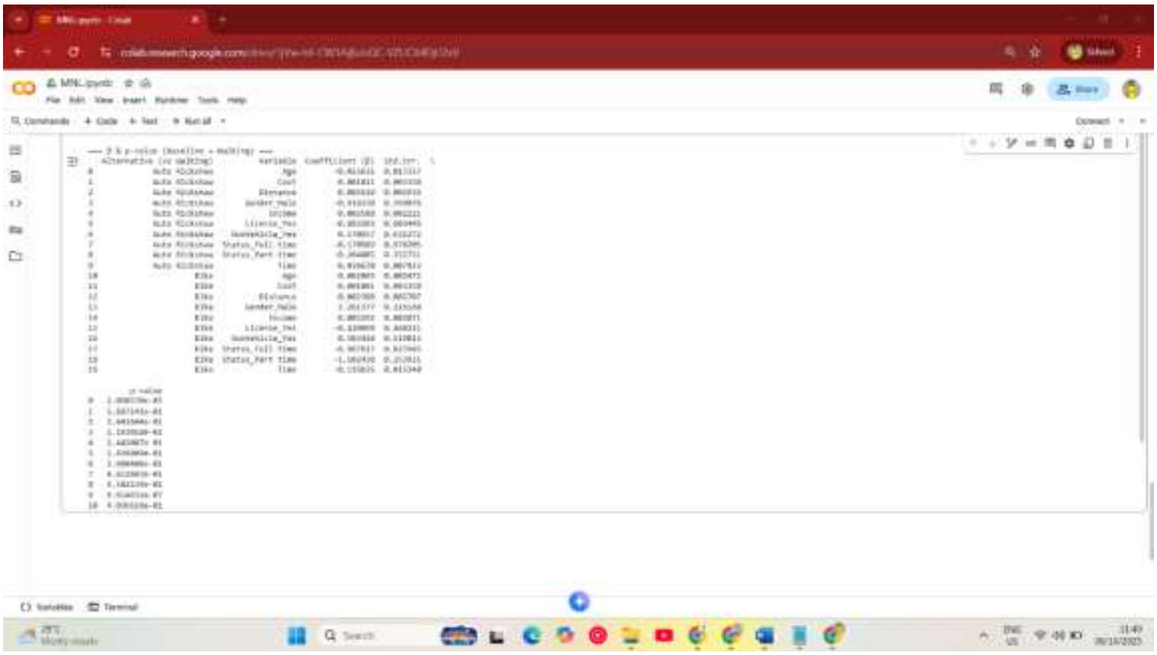

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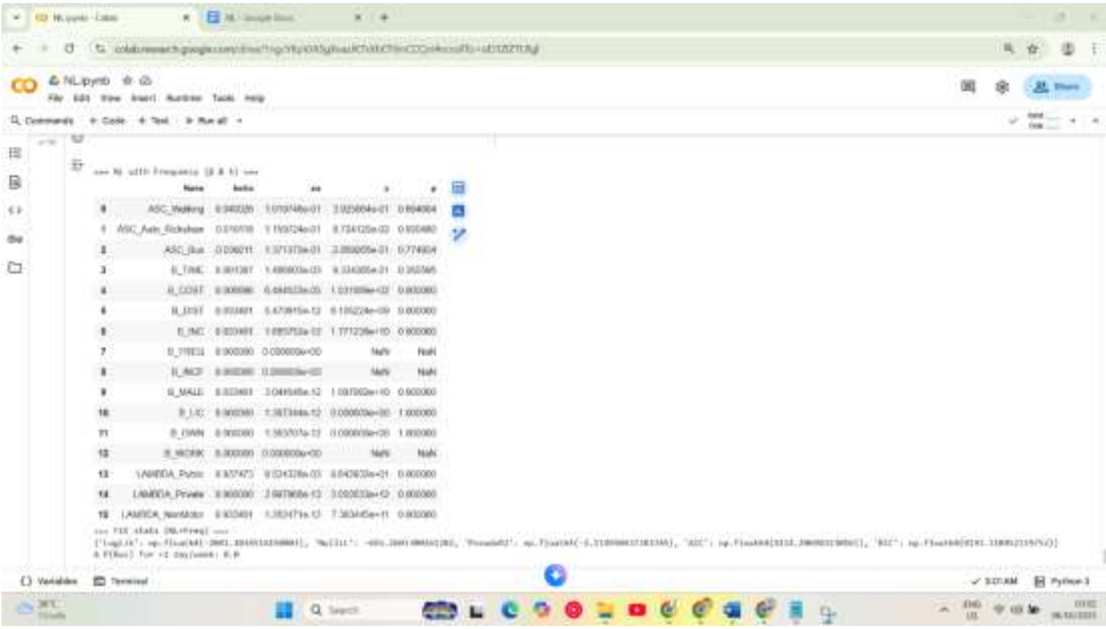

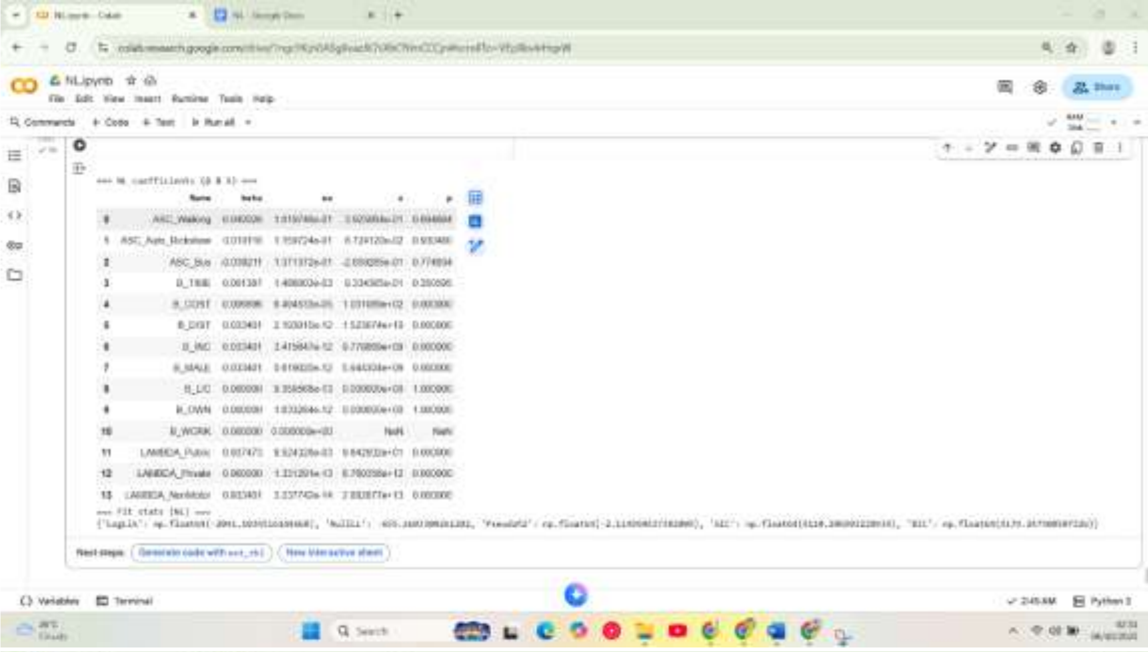

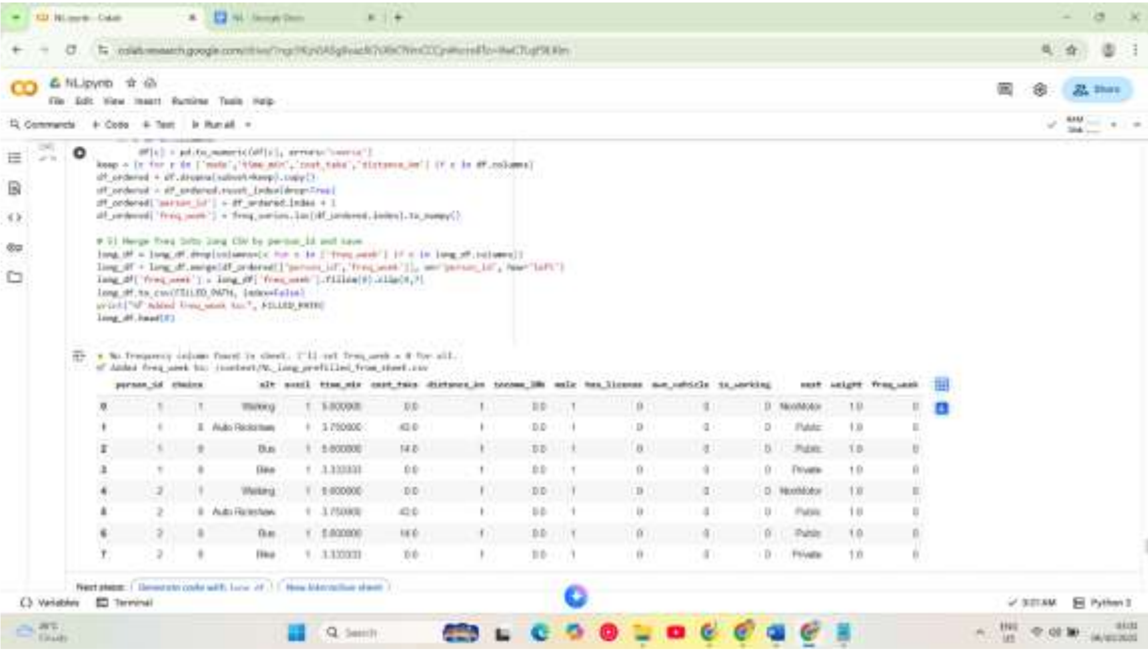

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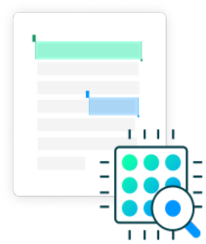

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