INTER-DISTRICT MODE CHOICE MODELLING OF RESIDENT STUDENTS OF BUET

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ABSTRACT

In a rapidly growing country like Bangladesh, understanding the mode choice behavior of university students is crucial for effective urban and transportation planning. This study explores the heterogeneity in the mode choice of residential students of BUET, through a revealed preference questionnaire survey across five modes: non-airconditioned bus, air-conditioned bus, train, owned cars, and rented cars. The methodological framework was based on Utility Maximization Theory, which resulted in a multinomial logit model (MNL). This model unraveled the combination of parameters that represented the most accurate mode selection. Among public transportation modes, bus had a higher elasticity value for travel cost which suggested a high-cost sensitivity, while AC bus users were extremely time sensitive. This difference became even clearer in the Value-of-Time (VOT) estimations. Auto ownership was proven to be the most dominant predictor of private car usage. The model revealed a strong gender dimension where female students showed a greater inclination towards modes that had higher perceived safety and comfort (AC bus and personal cars). Additionally, this model identified the distinct effect of family income of a student on car ownership and personal income on the use of rental cars. This research provides practical takeaways that policymakers and urban planners can use for improving transportation infrastructure and enhancing the travel experience of all the inter-district commuters in Bangladesh.

Keywords: *Mode choice modeling, discrete choice model, travel behavior, university students, transportation preferences*

1. INTRODUCTION

1.1 Research Background and Motivation

In Bangladesh, public transportations are characterized by inadequacy and unreliability, failing to meet the travel demands exerted by this country's massive population, and the problem is acute when it comes to inter-district travel.

While university students are a significant part of the demographic that is involved in inter-district travel, the travel behaviors among all the university students are not uniform. Prior works focused on the general university student population or on private university populations (Nasrin, 2020), which led to a notable research gap in studies that are specifically on students who are from public or government-owned universities. This particular demographic is significantly different from private university students in many aspects, including socio-demographic background, financial constraints, and most importantly, mode preferences during long-distance travel. Such variations are often crucial, as these students are choosing various travel modes frequently while balancing affordability with comfort, safety, and convenience.

1.2 Determinants of Mode Choice Among Students

Previous literature has shown that the factors that predominantly influence travel decisions are affordability, accessibility, comfort, and trip distance (Tiwari & Jain, 2012; Shukla & Gadani, 2021). Gender-based safety concerns have also proven to be critical, as female passengers often feel unsafe when traveling alone, especially at night (Zohir, 2003; Hoque et al., 2020). This concern motivates many female students in Bangladesh to prefer AC buses and trains where separate seating and stronger security arrangements are available (Mandhani et al., 2021; Pourhashem et al., 2019). Furthermore, researchers have noted that rising family incomes are gradually shifting preferences toward more comfortable inter-district travel options such as premium bus services or rented cars (Nasrin, 2020; Rahman, 2020), though the choice remains heavily cost-dependent for many students.

Another important aspect of inter-district mobility is infrastructure variation across regions(Mahmud 2012). Students traveling to rural or remote districts often face additional barriers such as poor road conditions, limited transport availability, longer travel hours, and the need for multiple transfers (Ahmed & Hossain, 2021). Congestion at Dhaka's entry points and on major corridors can also distort typical relationships between travel distance and travel time (Yasmin et al., 2006). Recent digital shifts, including online ticketing platforms like Shohoz and Bdtickets, are now influencing mode availability perceptions by reducing waiting times and increasing the likelihood of securing seats during peak periods, but these technological effects remain understudied in student travel behavior. Infrequent travelers, such as inter-district students, tend to value travel comfort disproportionately.

Nicolaidis (1975) positioned comfort as a latent utility dimension. Transportation modes that offer seat reservation are often preferred for predictability (Rahman, 2020). Socioeconomic variables such as gender, income level, and car ownership also influence mode selection. Higher-income students tend to favor private transportation options (Khattak et al., 2011), whereas those from lower-income households rely more heavily on buses and trains. Guliani et al. (2015) found that students with access to a private vehicle are significantly more likely to use it, and that car ownership also alters how individuals perceive and weigh time or cost constraints.

1.3 Methodological Approaches in Mode Choice Studies

To analyze travel decisions, discrete choice models such as the Multinomial Logit (MNL) framework have been widely adopted (Zhan et al., 2016; Pavlyuk & Gromule, 2011). The Multinomial Logit (MNL) model, based on Random Utility Theory (Manski, 1977), is a common choice for its simplicity and interpretability in mode choice studies. Many researchers have extended MNL to include more complex effects or nested structures when needed (Chandra & Chalumuri, 2014). These models are especially suited for capturing mutually exclusive decisions among finite options like an AC bus, a regular bus, or a train. Prior work (Rodríguez & Joo, 2004; Whalen et al., 2013) has effectively applied MNL models to student datasets in both urban and intercity contexts, highlighting how preferences cluster around affordability, travel time, and comfort.

Recent studies on university populations have applied MNL successfully: Whalen et al. (2013) modeled student commute mode choices and highlighted the role of active travel options, while Lodhi & Rana (2021) used MNL for educational trip mode choice in Pakistan, noting socio-cultural factors unique to that setting. In Bangladesh, Saha et al. (2010) developed a mode choice model for Dhaka's urban traffic, and Yasmin et al. (2006) specifically studied Dhaka University students' mode choice for city travel. These efforts provide valuable background, but none have addressed inter-district (inter-city) travel by students.

The MNL approach is also favored for its interpretability and estimation efficiency. This study leverages this model to capture the revealed preferences of students using robust econometric estimation, following a similar methodological rigor seen in Nguyen-Phuoc et al. (2018) and Zhao et al. (2020).

1.4 Research Objectives

Building on the motivation in Sections 1.1, 1.2, and 1.3, this research investigates the mode choice behaviour of BUET residential students traveling from Dhaka to their hometowns. This study focuses on finding a combination of economic, demographic, and travel-related factors that can shape the decisions of the students among commonly used transportation modes in Bangladesh.

To that end, the major objectives of this research include developing a robust Multinomial Logit model, identifying the factors that motivate mode choice and the extent to which these variables influence the mode choice decision, and finally providing practical takeaways to policymakers and urban planners to design more efficient, equitable, and sustainable transportation systems.

2. DATA

2.1 Survey Design & Data Collection

A Revealed Preference (RP) survey was designed to collect information regarding the students' most recent trip from their dormitory in Dhaka to their home district. The survey was structured to collect data in three main sections. The first section inquired about the trip characteristics, such as the chosen mode, total travel time, total travel cost, and travel distance. The second section queried regarding socio-economic characteristics like age, gender, family income, and personal income. The last section of the survey included questions about perceived levels of comfort and safety for their chosen mode.

A total of 241 valid responses were collected over a span of 2 months from the resident students of BUET through a combination of online and in-person surveys. This sample size was found to be appropriate upon using Slovin's formula with a 7% margin of error and 95% confidence level. Initially, the survey contained 8 transportation modes as alternatives. However, based on the analysis of survey data, five distinct modes were identified to be the viable alternatives for the model: Bus, Air-conditioned Bus, Train, Personal Car (Owned), and Rental Car.

2.2 Descriptive Analysis of Collected Data

The descriptive summary of the demographic data collected from 241 resident students of BUET is given below in Table 1. The table represents the demographic distribution of the surveyed respondents. 24.3% of the respondents were female students, and 75.7% of them were male students. The research group tried to increase the percentage of female students, but it was difficult as BUET typically has a lower percentage of female students (not more than 20%). Almost 100% of the respondents belonged to the age group of 19 to 24 years, which is the typical age of undergraduate students in Bangladesh. Among the respondents 38% had a family income between 30 to 50 thousand taka (BDT). Roughly 20% had a family income of less than 30 thousand taka (BDT). Among the rest of the participants, 24% had a family income between 50 to 80 thousand taka (BDT), and the rest had a family income over 80 thousand taka (BDT). A similar distribution is shown for the student's personal income (private tuition, part-time jobs, etc) in Table 1.

The most dominant among the chosen modes were Bus (48.2%), followed by AC Bus (25.9%). Together, these two modes accounted for almost three-quarters of all the trips, which identifies the significance of bus services for this particular demographic. Remaining modes, Personal Car (9.8%), Train (10.1%), and Rental Car (6%) represented smaller but meaningful market segments.

Variable	Category	Percentage
	Male	75.70%
Gender	Female	24.30%
	Bus	48.20%
	AC Bus	25.90%
	Train	10.10%
	Personal Car	9.80%
Mode Choice	Rental Car	6%
	10,000-20,000 Tk	8.70%
	20,000-30,000 Tk	11.00%
	30,000-50,000 Tk	38.10%
	50,000-80,000 Tk	24.30%
Family Income	More than 80,000 Tk	17.90%
	Less than 5,000 Tk	13.30%
	5,000-10,000 Tk	16.80%
	10,000-15,000 Tk	41.00%
	15,000-20,000 Tk	12.70%
Personal Income	More than 20,000 Tk	16.20%

Table 1: Demographic Distribution of Survey Respondents

2.3 Level of Service Data Augmentation from Google Maps

During the RP survey, respondents reported only the travel time and cost for their chosen mode. To compare the attributes of all available alternatives, travel time and travel distance were required, but deriving them was challenging. Because those values were not always reported, we programmatically derived distances and times and then computed fares or generalized costs by mode. For road-based modes, we used the Google Maps Distance Matrix in driving mode to obtain the distance and travel time information for different modes. The API returns distances and durations, but no information on fares, so fares needed to be computed externally. For the train, scheduled in vehicle times were taken from Bangladesh Railway intercity timetables, and class-specific fares were read from the official zone fare lists, cross-checked against the Railway portal.

For inter-district bus fares, we used the government per-kilometer schedule issued by Bangladesh Road Transport Authority (BRTA) (BRTA, 2022), which sets a baseline of Tk 2.20 per kilometer on long-distance routes with a minimum fare, noting that AC buses often price above this baseline. For a personal private car, we converted distance to generalized cost using typical fuel prices, and added applicable tolls such as the Padma Bridge toll when the route crossed tolled infrastructure. We priced the rental car alternative using typical market rates obtained from multiple Dhaka rental websites. We validated the travel times extracted from the API for the chosen mode against those reported by the respondents during the survey. The comparison revealed a good resemblance between the two data sources for the chosen modes.

Mode	Distance (km)	Time (min)	Fare (BDT)
Bus(non-AC)	Google Distance Matrix API, mode=driving	Google Distance Matrix API, mode=driving	2.2 BDT/km in BDT, per BRTA long distance schedule.
Bus(AC)	Google Distance Matrix API, mode=driving.	Google Distance Matrix API, mode=driving	Operator(Shohoz and Bdtickets) quotes for the OD pair during the survey window
Train	Railway route between OD stations	Bangladesh Railway intercity timetable scheduled time	Official class-based fare from the Railway zone fare list
Personal Car	Google Distance Matrix API, mode=driving	Google Distance Matrix API, mode=driving	Typical fuel price set by Government(per km) × Distance(km) + toll price
Rental Car	Google Distance Matrix API, mode=driving	Google Distance Matrix API, mode=driving	Median of Dhaka rental operator prices

Table 2. Level of service of different modes

3. METHODOLOGY

3.1 Formulation of Multinomial Logit Model (MNL)

The methodological framework of this study is based on Utility Maximization Theory which proposes that n will choose the alternative i from a set of available alternatives J that provides the highest perceived utility. The utility U that the individual derives from choosing alternative i is composed of a systematic (observable) component V and a random (unobservable) error term ε and can be presented in equation (1) below:

$$U_{ij}= V_{ij}+ \varepsilon_{ij} \tag{1}$$

This study involved using a Multinomial Logit (MNL) model, which assumes the error terms are independently and identically distributed (IID) with a Gumbel distribution. The deterministic portion of the utility equation, V, which could be a function of the characteristics of the decision maker and the attributes of the alternatives follows:

$$Vni = ASCi + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_n X_n \quad (2)$$

Where *ASCi* is the Alternative-Specific Constant for mode *i*, X_n represents the explanatory variables such as, travel cost, travel time, gender etc. and β are the parameters to be estimated.

3.2 Model Development Strategy

We started with a baseline model that contained the Alternative Specific Constants (ASCs) only where the transportation mode, Bus, was considered as the reference alternative. This model captured the intrinsic preference for other modes relative to the bus while ignoring other trip attributes. This model indicated that it was necessary to introduce explanatory variables beyond inherent tastes.

Building on the baseline model, we iterated through thirteen models in a stepwise manner in order to achieve our final model. At each step, we monitored the changes in log-likelihood, AIC, BIC, and adjusted ρ^2 of the model. We examined the values of the estimated parameters and t-statistic values to judge the sign and significance. To our baseline model, we at first added the travel time, which had the expected negative effect. Successively, we added travel cost, then travel distance to analyze whether longer trips shift the preferences towards expensive and more comfortable modes. In the next step, we introduced gender terms for each mode to assess if different genders respond differently to available transportation modes. The income effect was explored after that by adding family income and personal income of the students. In the next step, we tried to acknowledge the effect of comfort in longer trips.

We then introduced a low-income adjustment parameter to reveal the affordability constraints, and finally added auto ownership to represent both availability and the tendency to pick private modes. Across these steps, we kept only the variables that improved fit and made behavioral sense, and dropped the ones that did not, aiming for a compact, interpretable specification until we reached our final model.

4. MODEL ESTIMATION RESULT

4.1 Final Model Specification and Overview

This section represents the results of the final multinomial logit (MNL) model developed to analyze the inter-district mode choice behavior of the resident students of BUET. As mentioned in the preceding section, the final model was achieved through a stepwise refinement procedure where we progressively removed the insignificant variables to arrive at the most parsimonious, statistically significant, and behaviorally sound model.

The estimation is based on the "Bus" mode acting as the base alternative for interpretation. Therefore, all the estimated parameters represent the change in utility for a given mode relative to the standard, non-AC Bus. For this study, parameters are considered statistically significant if they have an absolute value of t-statistics that exceeds 1.96(95% confidence level). However, given the real-world behavioral context and the exploratory nature of our research, we have considered the variables to be significant that had a t-statistic value that exceeded 1.65(90% confidence level) as they offered meaningful behavioral insights.

The result of the final model is represented in **Table 3**. This model showed a strong goodness-of-fit, achieving an Adjusted Rho-Squared (adjusted ρ^2) of 0.4724, which is indicative of a robust model with high explanatory power for a discrete choice model of this nature.

	Modes									
Variables	**Bus (Base)**		**AC Bus**		**Train**		**Personal Car**		**Rental Car**	
	Estimate	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Alternative Specific Constants										
Alternative Specific Constants	0	---	-0.831	-0.773	0.879	2.23	-3.444	-1.87	-1.866	-2.17
Level-of-Service (LoS) Attributes										
Travel Time (min)	-0.159	-1.65	-0.688	-2.23	-0.185	-1.87	---	---	-0.374	-2.38
Travel Cost (BDT)	-0.229	-2.95	-0.015	-2.69	---	---	---	---	---	---
Trip Attributes										
Distance(km)	---	---	0.743	3.04	0.6335	2.65	---	---	-1.4969	-2.75
Socio-Demographic & Economic Attributes										
Gender (Female)	---	---	0.655	2.02	-0.375	-1.43	1.216	2.97	1.076	3.01
Family Income	---	---	-0.279	-1.68	---	---	5.687	1.78	---	---
Self-Income	---	---	---	---	-0.151	-1.77	---	---	0.325	3.33
Low-Income Factor	-1.536	-1.96	-1.536	-1.96	-1.536	-1.96	-1.536	-1.96	-1.536	-1.96
Latent Preferences & Ownership										
Comfort Level	---	---	0.548	3.51	---	---	5.979	1.76	0.482	2.91
Comfort-Income Interaction	---	---	---	---	---	---	-0.951	-1.67	---	---
Auto Ownership	-0.244	-1.77	-0.244	-1.77	-0.244	-1.77	---	---	-0.244	-1.77
Number of Observations	241									
Number of Estimated Parameters	27									
Adjusted Rho-square	0.4724									
Final Log Likelihood	-365.87									
AIC	785.74									
BIC	879.83									

Table 3. Multinomial logit model results of mode choice model

4.2 Interpretation of Model Attributes

4.2.1 Alternative Specific Constants (ASCs)

The Alternative Specific Constants(ASCs) represent the intrinsic preference for each mode relative to the base mode "Bus" when all the explanatory variables are held at zero. The results presented in Table

3 show a positive and highly significant ASC for Train, which indicates that ceteris paribus, students have a strong inherent preference for choosing train over base mode(Bus) for their inter-district trips. This reference can be attributed to a variety of unobserved factors, such as avoidance of road congestion, etc.
Both Personal Car and Rental Car, on the contrary, have significant negative ASCs, which does not imply that students dislike these modes; rather, it means that the baseline barriers to using these modes are high. This can be due to the absence of powerful enabling factors like high family income, preference for comfort, or existing car ownership that promotes the use of these private modes.

4.2.2 Level of Service (LoS) Attributes

Travel cost and Travel Time coefficients for all the modes are negative, which were expected as increased cost and increased travel time for any transportation mode will discourage consumers from using those modes, hence resulting in reduced utility.

These travel cost coefficients were significant for both the Bus and the AC Bus. This indicated that the demographic of BUET resident students is highly sensitive to price, and any increase in the fares of either of the bus modes will significantly reduce their utility and the probability of being chosen. This finding reinforces the importance of affordability for this population, a fact that was also highlighted in the descriptive statistics.

Travel time coefficients remained significant for all modes except for Personal Cars. The disutility of travel time was found to be most prominent in magnitude for the more comfortable and premium modes like AC Bus and Rental Car, which is a highly logical finding. Students who are willing to pay a significant monetary premium for an air-conditioned bus or private rental cars are also, by extension, paying for the speed and convenience. Therefore, they are the most sensitive to failure in service, like increased travel time. On the contrary, the economic modes like Bus and Train were less sensitive to time. This indicates that the users of these modes are "captive" audiences. The primary driver for selecting these modes was likely to be cost-saving, and so the students are more tolerant of longer travel times if the cost remains low.

4.2.3 Trip Attributes

Beyond the travel time and travel cost, the model further included trip distance as a key variable to reveal the difference among how different transportation modes are perceived for long-distance inter-district trips versus shorter trips. The coefficients for travel distance were positive and highly significant for both AC Bus and Train, which means the utility of these modes relative to the base alternative Bus increases with the increase of travel distance. This finding is justifiable as regular buses are only tolerable for shorter trips due to the perceived discomfort that will only be increasingly acute with the increase in long-haul trips. To this end, students prefer comfortable modes like the AC Bus for their cross-country trips. The Rental Car, on the contrary, had a strongly negative coefficient, which can be due to high travel costs, which can also be variable (fuel, toll) during long-distance trips.

4.2.4 Socio-Demographic and Economic Attributes

This cluster contains variables that are powerful in describing the underlying socio-economic structure that affects the choices available to different students.

4.2.4.1 Gender

Gender was proven to be a powerful predictor of mode choice. The Gender coefficients were positive and significant for AC Bus, Personal Car and Rental Car. Given that, the "female" gender was coded 1, these coefficients mean that female students have a significantly higher likelihood of choosing any of these three modes over the base "Bus" mode. This is a logical finding as the perceived safety and comfort are higher for these three modes compared to the crowded, exposed, and often chaotic nature of a regular public bus or train.

4.2.4.2 Income

This model used three distinct income-related variables that provided a highly insightful picture of affordability and financial constraints.

Family income variables act as a substitute for generational wealth and the ability to afford high-cost capital items. The coefficient of family income for Personal Car was significant and highly positive. This suggests that the use of a Personal car, a mode that is associated with high fixed and operating costs, is almost entirely dependent on high family income.

The personal income coefficient captures the effect of a student's own disposable income on the mode choice. It has a significant positive effect on Rental Car and a corresponding negative effect on Train. This reveals the realization that family wealth enables owning a car (Personal Car), while a student's own earnings enable renting one (Rental Car).

To address the low-income constraints, a variable was applied to the "economy" modes (Bus and Train). This variable was formulated as the inverse of family income. The negative coefficient, therefore, means that as family income decreases, the utility of choosing a Bus or Train increases. This finding indicates that students from lower-income households are not necessarily choosing these modes based on preference rather they are constrained into them by affordability.

4.2.5 Latent Preference and Ownership Effect

The estimated parameters for comfort were highly significant and positive for AC Bus, Personal Car, and Rental Car. This finding connects the qualitative data on comfort gathered through the questionnaire survey to the quantitative choice model. These parameters indicate that students who value comfort are significantly more likely to choose AC Bus, Personal Car, and Rental Car.

The interaction between comfort and income was introduced in the model through a complex interaction term and was applied to the utility equation of the Personal Car. This term is the product of a student's comfort preference and their family income. The negative coefficient is a nuanced but crucial finding. It means that the positive effect of comfort on choosing a personal car is reduced as family income increases. This may seem counterintuitive, but it suggests a saturation effect. For students from extremely wealthy families, the decision to use a personal car is based on simple availability and social status. The concept of choosing for comfort is a more powerful predictor for the middle-to-upper-income student, for whom this is a conscious trade-off.

Auto Ownership is applied to all modes except Personal Car. The negative coefficient portrays the powerful and expected availability effect. It suggests that if a student's family owns a car, the utility of all other modes (Bus, AC Bus, Train, and Rental) decreases significantly. Their access to a free (at the point of use), highly convenient, and comfortable alternative makes all other fee-based, schedule-bound options less attractive.

4.3 Elasticity Analysis and Value of Time

In this section, we present an analysis of elasticities and value-of-time (VOT) based on the final MNL model. We evaluated the ridership sensitivity of each mode to travel time and cost (direct elasticities). We also tried to figure out how the price change of one mode affects the ridership of the other (cross elasticities), and the implied economic values, such as the value of travel time (VOT). The analysis focuses on the Bus, AC Bus, and Train alternatives (the primary public transport modes), consistent with the final model's emphasis on these modes.

4.3.1 Direct Elasticities of Travel Time and Travel Cost

Direct (own-attribute) elasticity measures the percentage change in the probability of choosing a mode in response to a 1% increase in one of its own attributes (such as travel time or cost). **Table 4** presents the direct elasticities for travel time and travel cost for the Bus, AC Bus, and Train alternatives. These values are computed using the final model's coefficients and average travel time and cost for each mode.

Mode	Travel Time Elasticity	Travel Cost Elasticity
Bus	-0.47	–0.61
AC Bus	-4.23	–0.24
Train	-1.01	~0.00

Table 4. Direct Elasticity of Mode Choice Probability w.rt. Travel Time and Cost

Bus users are highly cost-sensitive, meaning fare increases significantly reduce ridership, while their time sensitivity is moderate. AC Bus users are extremely time-sensitive but fare-insensitive, indicating they value speed and comfort more than price. Train users show moderate time sensitivity but no measurable cost response due to uniformly low fares.

4.3.2 Cross-Elasticity and Substitution Effects

Cross-elasticity analysis examines how a change in one mode's attribute (here, we focus on price) affects the probability of choosing other modes. This reveals where riders are likely to shift when one mode becomes less attractive. We simulate a policy scenario in which the AC Bus fare is increased by 10% and estimate how the ridership shares would redistribute across the available modes. **Table 5** summarizes the observed mode shares and the modeled changes in probability for each mode due to the 10% AC Bus fare increase.

Mode	Observed Share	Cross-Elasticity wrt. AC Bus	Change in Probability (ΔP)
Bus	48.2%	+0.083	+0.40 percentage points
AC Bus	25.9%	-0.24	-0.62 percentage points
Train	10.1%	+0.079	+0.08 percentage points
Personal Car	9.8%	+0.082	+0.08 percentage points
Rental Car	6.0%	+0.083	+0.05 percentage points

Table 5. Ridership Redistribution if AC Bus Fare Increases by 10%

A 10% AC Bus fare increase reduces its market share by 0.62 percentage points and this lost share is redistributed proportionately to mainly to Bus and modestly to Train and Car modes. Cross-elasticities range from +0.079 to +0.083, indicating weak but proportional substitution.

4.3.3 Value-of-Time Estimation

The Value of Time (VOT) reflects how much travelers are willing to pay to save one hour of travel. It is computed as the ratio of the marginal utility of time to the marginal utility of cost, adjusted for model scaling:

$$\boldsymbol{VOT = \frac{\beta(time)}{\beta(cost)}}$$

For Bus, the VOT is approximately 6.94 BDT/hour which suggests that users are highly cost-sensitive and students choose bus primarily for affordability, not speed. For the AC Bus, the VOT is 468.0 BDT/hour which suggests that those students who chose the AC Bus are willing to pay significantly for faster and more comfortable travel.

5. CONCLUSIONS

This study analysed the inter-district mode choices of resident BUET students using a revealed-preference survey and an MNL framework. This model captured how generalized cost, time, comfort, income, gender, and auto ownership influence preference among non-AC bus, AC bus, train, personal car, and rental car.

The key findings are multifaceted. Among all the modes, buses were predominantly chosen by students due to affordability whereas trains are preferred during longer and reliability-sensitive trips. The tendency to choose private modes is driven more by factors like comfort, convenience, and ownership, and is largely insensitive to the marginal costs of a trip. Female students lean toward options perceived as safer and more comfortable, such as AC buses and personal cars, while auto ownership strongly shifts choices away from public modes. This model draws a nuanced distinction between types of income. It revealed that family income is the key predictor of car ownership, while personal "self-income" is the key predictor of car rental. Furthermore, the model indicated that students from lower-income backgrounds are significantly more dependent on traditional bus and train services.

These findings provide meaningful insights for transportation planners and university administrations. Firstly, it can be inferred from the study that enhancing student discounts on public transport, particularly on AC Bus and Train services, is crucial for supporting the student body, especially those with financial constraints. Secondly, to attract a wider range of students and address the clear gender-based preference, investments in improving the perceived and actual safety, security, and comfort of train services are essential. This study serves as a strong foundation for future research and provides a valuable tool for better-informed policymaking in urban and inter-district transport planning in Bangladesh.

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