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Research Article

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Posted Date: November 12th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11168185/v1

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Additional Declarations: No competing interests reported.

Educational Travel Mode Choice and Mobility Inequality in a Secondary City with Predominant Informal Transport in Bangladesh

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Abstract

Educational institutions are major trip generators in urban areas, and student trips form a significant share of daily travel demand in rapidly urbanizing cities. This study investigates home-to-institution trip mode choices in Narayanganj, an industrial secondary city in Bangladesh where informal transport dominates urban mobility. The data were collected through a household interview survey covering all 27 wards of the city, collecting information on 823 students across different levels of educational stages. Mode choices among eight modes were modeled using multinomial logit and mixed logit frameworks. The results indicated that informal transport modes account for approximately 59% of educational trips, establishing them as a major component of the city's accessibility system rather than a substitute for formal public transport. Distance was found to be an important factor associated with students' choice of motorized transport modes. Travel patterns also changed significantly across educational stages, as school bus/van use declined from 32.3% at primary level to 1.0% at university level while local bus use rose from zero to 30.1%. Male and female students travelled statistically similar distances, yet female students were significantly less likely to use motorcycles and incurred a higher travel cost per kilometer. The mixed logit model identified that students differed in their sensitivity to travel distance when choosing between rickshaw and school bus/van. These findings highlight the relevance of informal transport regulation, institutional location, and differences in transport access when planning for educational mobility.

Keywords: educational travel; mode choice; mobility inequality; informal paratransit; mixed logit; secondary cities; Bangladesh

1. Introduction

The cities in South Asia are urbanizing rapidly, often quicker than their transportation system can be planned to keep up. As a result, formal public transport has become limited in many cities, and informal and semi-formal transport has emerged to fill these gaps, becoming an integral mode of transport for everyday commuting. Educational institutions play a particularly important role in this system, as schools, colleges, madrasahs, and universities generate large numbers of trips within relatively concentrated time periods. The everyday travel of students between home and an educational institution connects them with the wider urban transport system. The way the students make these trips affects the trip time and trip cost, as well as their ability to conveniently access educational opportunities [1–5].

Educational travel can therefore be viewed not only as a transport issue but also as a matter of urban accessibility. The transport options available to students affect how they travel to their educational institutions, while the distance between home and the institution influences the time, cost, and effort required for these daily journeys. However, these scenarios are not

experienced in the same way by all students. Factors such as gender, education level, household income, vehicle ownership, and access to different transport modes can influence the mobility options that students can realistically afford and use, even when they face similar travel needs. In this way, students' daily travel to educational institutions provides an important context for understanding differences in mobility and accessibility within cities.

Despite the relevance of these issues, existing research has several limitations. First, educational travel studies have mostly focused on primary and secondary school children, often treating educational trips as a childhood mobility problem. This leaves less attention to the transition from school to higher secondary and university education, when travel arrangements and available transport options may change significantly. Older students may increasingly use public or shared transport independently, while younger students are more likely to depend on parents, guardians, or organized transport. Analyzing students across successive educational stages within the same urban transport environment therefore provides an opportunity to investigate how mode choice changes as educational circumstances change.

Second, much of the existing evidence comes from cities where formal public transport, school bus services, walking infrastructure, or organized institutional transport constitute important components of the choice set. These conditions differ significantly from those found in many South Asian secondary cities, where informal paratransit plays a central role in everyday mobility. Autorickshaws, cycle-rickshaws, shared three-wheelers, human-haulers, and semi-fixed-route services can provide essential connections between households and educational institutions, but their operation, availability, affordability, and safety are often less directly integrated into formal urban transport planning. The consequences of this transport structure for educational mobility remain comparatively underexplored.

Bangladesh provides an important setting for analyzing these relationships. Its rapidly urbanizing cities have experienced considerable growth in population and travel demand, while informal transport modes remain an important part of urban mobility. Narayanganj is particularly relevant because it is a densely populated and highly industrialized secondary city located approximately 16 km southeast of Dhaka. Its transport system includes battery-powered autorickshaws, cycle-rickshaws, CNG-powered three-wheelers and tempos, local buses, private cars, motorcycles, and institutionally arranged school buses or vans. Educational travel therefore takes place within a heterogeneous transport environment in which formal and informal services coexist, but informal paratransit is particularly prominent.

The present study analyzes home-to-institution trips among students across five educational stages: primary, secondary, higher secondary, university, and madrasah education in Narayanganj City Corporation. This broader educational coverage allows the study to analyze how educational progression is associated with travel behavior within a common urban transport context. Educational level is considered an indicator of changing travel circumstances rather than a direct measure of individual autonomy. The analysis focuses on differences in transport mode use across educational stages and students' responses to travel distance.

The study also explores differences in mobility opportunities and travel burden among students. Gender is considered particularly important because males and females can choose different transport modes even when they travel similar distances. Household resources and vehicle ownership may also influence the set of transport options available to students. Instead of assuming that these characteristics directly determine travel behavior, the study investigates how they are associated with the transport modes students actually use within the local urban transport environment.

To capture both systematic mode-choice relationships and unobserved differences in distance sensitivity, the study estimates multinomial logit (MNL) and mixed logit (ML) models. The mixed logit framework allows distance sensitivity to vary across individuals for selected modes where heterogeneous user groups are theoretically plausible. The purpose of using the ML model is therefore not simply to introduce a more sophisticated statistical technique, but

to investigate whether different students respond differently to travel distance when choosing their transport mode.

The study has four objectives. First, it describes educational travel patterns and modal composition across different educational stages in Narayanganj. Second, it identifies the trip, individual, and household characteristics associated with the choice among eight transport modes. Third, it investigates whether distance sensitivity varies among students for selected modes. Fourth, it analyzes the urban-mobility implications of these patterns by comparing travel expenditures between male and female students with similar travel distances and by assessing how changes in the location of educational institutions could affect the choice of their selected transport modes.

2. Literature review

2.1 Educational travel as an urban accessibility issue

Educational travel represents an important component of daily urban mobility because educational institutions generate regular and concentrated travel demand. Previous studies have demonstrated that students' travel mode choices are associated with travel distance, travel time, cost, household characteristics, and individual socio-demographic characteristics [8–19]. Among these factors, distance is consistently identified as one of the strongest determinants of educational mode choice because it directly affects the feasibility of walking and cycling and increases the need for motorized transport. Studies from China, Sri Lanka, Pakistan, Türkiye, and other contexts have generally found that students travelling longer distances are more likely to use motorized modes [8–15].

However, the importance of distance extends beyond its role as a conventional explanatory variable. Distance determines the set of transport options that are practically feasible for a student. A short-distance trip may be completed on foot, whereas the same educational requirement at a greater distance may require a rickshaw, bus, motorcycle, car, or other motorized service. Consequently, the spatial distribution of educational institutions can influence not only travel demand but also the transport burden experienced by different groups of students.

Educational travel is also closely related to household decision-making. Younger students may depend on parents or guardians to determine how they travel, while older students may increasingly make travel decisions independently. Previous research has shown differences in travel behavior between children and youth and across educational settings [12,19]. Nevertheless, studies commonly explore specific age groups or educational categories separately. Investigating multiple educational stages within the same city can provide a clearer picture of how mode choice changes as students progress through the educational system.

2.2 Mobility inequality and unequal transport opportunities

Urban mobility is not experienced uniformly across social groups. Mobility inequality can arise when individuals with similar travel needs face different feasible, affordable, or socially acceptable transport options. In educational travel, such differences may affect how students reach institutions, how much they spend on travel, and which institutions are accessible from their homes.

Household income and vehicle ownership are frequently associated with differences in travel behavior. Evidence from several countries indicates that access to private vehicles increases the availability of motorized travel options, while students without private transport are more dependent on walking, public transport, and shared services [8,10–12,14,18,19]. However, household income alone does not necessarily capture the full range of mobility opportunities. Vehicle ownership, gender, institutional location, and the availability of particular transport services may jointly determine which alternatives are practically accessible.

Gender represents another important aspect of mobility inequality. Studies of educational travel in South Asia and other regions have identified gender differences in mode choice, often

linking these differences to perceived safety, security, social expectations, and restrictions on independent mobility [6,10–16]. Such mechanisms are particularly important in settings where public and informal transport services provide different levels of privacy, security, and social acceptability. Importantly, observed gender differences in mode choice do not necessarily imply differences in travel requirements. Two students may travel similar distances but have access to different transport options, resulting in different travel costs or levels of mobility.

This distinction is important for urban policy. If mobility differences arise primarily because one group travels shorter distances, improving spatial accessibility may significantly reduce the disparity. If, however, students travel similar distances but use different transport modes because some alternatives are less accessible or acceptable to particular groups, spatial planning alone may not eliminate the inequality. Educational travel mode choice can therefore provide an empirical lens for identifying how transport systems distribute mobility opportunities across students.

2.3 Informal transport and educational mobility in rapidly urbanizing cities

The role of informal transport is becoming particularly important in low- and middle-income cities, where formal public transport systems may not provide comprehensive spatial coverage. Informal and semi-formal services can provide flexible and relatively accessible connections between residential areas and educational institutions. Evidence from Bangladesh, Pakistan, Sri Lanka, and Sierra Leone demonstrates the importance of paratransit, motorcycles, shared vehicles, and other intermediate modes in student mobility [12,13,20].

The transport environment in these cities differs from that of many developed-country settings. Studies in North America and Europe frequently examine walking, cycling, formal public transport, private vehicles, and organized school bus services [18,21,22]. In contrast, students in South Asian cities may depend on combinations of auto-rickshaws, cycle-rickshaws, CNG three-wheelers, tempos, motorcycles, local buses, and privately arranged school transport. These modes may differ significantly in cost, flexibility, capacity, safety, and spatial coverage.

Informal transport should therefore not be viewed simply as a replacement for formal public transport. In many secondary cities, it constitutes a structural component of the urban mobility system. Its role may be particularly important for educational travel because students require reliable daily access to institutions, while families may select different services depending on distance, age, gender, and household circumstances.

Despite its importance, the interaction between educational progression and informal transport remains not well understood. In particular, there is limited evidence on whether students at different educational stages depend on different types of informal transport modes and whether their sensitivity to travel distance differs across modes. Understanding these relationships is important for secondary cities where replacing informal transport with formal services may not be feasible in the short term.

2.4 Gendered mobility and educational access

Gender can influence educational travel through differences in perceived safety, social acceptability, transport availability, and household decision-making. Previous research has reported that female students may be less likely to use particular forms of independent or open public transport and may depend more heavily on escorted, shared, or organized services [6,10–16]. These differences have been associated with concerns about traffic safety, personal security, harassment, and social expectations surrounding independent travel.

The implications go beyond transport mode shares. If a particular mode is less accessible to one group, students may have to use other modes that are more expensive or take longer travel time. Therefore, differences in mode choice between male and female students may reflect differences in their available transport options rather than simply differences in personal preference.

2.5 Mode choice and heterogeneous distance sensitivity

Traditional multinomial logit models are useful for analyzing educational travel mode choice, but they generally assume that students respond to travel factors in the same way. But students using the same mode may differ in how strongly distance affects their choices. Mixed logit models address this limitation by allowing selected parameters to vary across individuals and have increasingly been used to represent unobserved preference heterogeneity [12,15,26,31].

The relevance of heterogeneous distance sensitivity is particularly clear in educational travel. The same transport mode may serve students with very different travel circumstances. For example, a rickshaw may be used for short trips by older students who travel independently, while a younger student may use the same mode because it is chosen by their parents, even for a longer journey. Similarly, school bus services may be used by the students who are willing to travel farther to access a preferred institution. A single average distance coefficient may therefore overlook the differences in how the students respond to spatial separation between homes and institutions.

Understanding this heterogeneity is important for urban transport planning because changes in institutional location or residential areas may affect students differently depending on how sensitive they are to travel distance. The mixed logit model therefore helps identify whether such differences exist and provides a better understanding of how changes in travel distance may influence educational travel patterns.

2.6 Research gap and contributions

The literature reviewed above indicates three interconnected gaps. First, educational travel research has often investigated school-aged children and university students separately, limiting understanding of how mode choice changes across successive educational stages. Second, relatively little empirical evidence is available from secondary cities in Bangladesh and other South Asian contexts where informal transport constitutes a major part of the urban mobility system. Third, although heterogeneous travel preferences have been considered in mode-choice research, less attention has been given to how students using informal and semi-formal transport respond differently to travel distance.

This study addresses these gaps by investigating students across primary, secondary, higher secondary, university, and madrasah education within the same urban transport environment. The analysis contributes in three ways. First, it shows how modal patterns change across educational stages rather than focusing on a single school-age population. Second, it demonstrates how informal paratransit functions as a major mode of transport for educational mobility in a rapidly urbanizing secondary city. Third, it investigates whether students differ in their sensitivity to travel distance across selected modes.

The study further investigates these findings from a mobility inequality perspective. Rather than viewing mode choice simply as an individual preference, the analysis considers whether students traveling similar distances have different transport options and accessibility levels. This perspective connects discrete choice modelling with broader issues of urban accessibility and equity.

3. Methods

3.1. Study area

Narayanganj City Corporation (NCC), commonly known as the "Dundee of the East," is an industrial city situated 16 km southeast of Dhaka, the capital of Bangladesh, at the junction of the Shitalakshya River. The city is one of the most densely populated urban areas in Bangladesh, with a population of over 967,887, consisting of 27 wards covering an area of approximately 47.07 square kilometers. Narayanganj serves as a major commercial and industrial hub, hosting garment manufacturing, jute processing, and small and medium enterprises. Out of the total population in the city, approximately 214386 people are reported to be students aged between 5 and 29 years [24]. In the vicinity of the NCC, there are roughly 182 educational institutions (Local Government Engineering Department, 2025) for students in Narayanganj city, and to avail themselves of better-quality education, a portion of students

travel from Narayanganj to institutes in Dhaka every day. The most dominant mode of transport in the city is the battery-powered auto rickshaw, which people of all classes use; besides, several other modes are available for students to travel to and from institutions, which include rickshaw, school bus, school van, public bus, private car, motorcycle, and walking.

3.2. Questionnaire design and data collection

A structured questionnaire was developed comprising three sections: (1) student-level characteristics including gender, age, and education level; (2) household-level characteristics including monthly household income group, car ownership (binary), and motorcycle ownership (binary); and (3) trip-level information including travel mode, one-way home-to-institution distance (km), one-way daily travel cost (BDT), and travel time (minutes). Respondents identified their primary mode from: auto/easybike, public transport (local bus), private car, CNG-driven three-wheeler or human-hauler, motorcycle, rickshaw, school bus or van, bicycle, and walking.

The travel data were collected through a household interview survey conducted in the study area on a representative sample of households covering all 27 wards of Narayanganj City Corporation (NCC). Survey samples were selected using a stratified random sampling framework, with a total of 2040 households surveyed in NCC. Sampling intervals were set at 10-metre intervals, though these were adjusted to accommodate differences in geography, settlement, and population distribution at the ward level. A total of 830 samples of students were collected from the survey. The use of bicycles is excluded from the discrete choice analysis because only seven students reported this mode. The distribution of responses across education levels, genders, household income groups, and travel modes is summarized in Table 1.

Table 1 Summary of survey responses

Item	Category	N	%
Gender	Male	499	60.6
	Female	324	39.4
Education level	Primary (Grade 1–5)	93	11.3
	Secondary (Grade 6–10)	283	34.4
	Higher Secondary (Grade 11–12)	156	19.0
	University	209	25.4
	Madrasah	82	10.0
Household income	Low (< BDT 15,000/month)	281	34.1
	Lower-middle (BDT 15,001–30,000)	325	39.5
	Upper-middle (BDT 30,001–50,000)	127	15.4
	High (> BDT 50,000)	90	10.9
Vehicle ownership	Car (yes)	77	9.4
	Motorcycle (yes)	214	26.0
Travel mode	Auto/ Easy bike	284	34.5
	Local bus	108	13.1
	Private Car	30	3.6
	CNG / Human-hauler	40	4.9
	Motorcycle	30	3.6
	Rickshaw	162	19.7
	School bus / van	76	9.2
	Walking	93	11.3

3.4. Analysis methods

The data analysis proceeded in two phases. In the first phase, descriptive statistics are analyzed for all continuous variables such as home-to-institution distance, one-way travel time, travel cost, and student age, which are compared across modes using boxplots, bar charts, and mode-specific mean and standard deviation summaries. Non-parametric hypothesis tests are used to evaluate whether the observed differences in trip characteristics across modes and between sociodemographic subgroups were statistically reliable. The Kruskal-Wallis H test is applied to assess whether the central tendency of a continuous variable differed across the eight mode groups; the Mann-Whitney U test is used for planned pairwise comparisons. These rank-based tests are preferred over parametric alternatives because the distributions of travel distance and cost exhibited pronounced positive skewness, violating the normality assumption of analysis of variance. In the second phase, discrete choice models are used to identify the sociodemographic and trip-level factors that determine mode choice decisions. It assumes that a q-decision maker (q = 1,…, Q), who needs to choose among i alternatives, assigns to each alternative a Uiq utility function which is specified in Eq. 1.

$$U_{iq} = V_{iq} + \varepsilon_{iq} \quad (1)$$

where V_{iq} is the deterministic component and ε_{iq} is the random term of the utility function. V_{iq} can have different terms, but a linear specification is used in this study as shown in Eq. 2.

$$V_{iq} = \sum_j \beta_{ij} X_{iqj} \quad (2)$$

where X_{iqj} represents the j attributes of alternative i as perceived by decision-maker q, and β_{ij} are the corresponding parameters to be estimated. It is possible to demonstrate that the P_{iq} probability that a q decision-maker chooses alternative i has the form shown in Eq. 3, which is the formulation of a classic multinomial logit model, if assuming that the random terms in Eq. 1 follow Gumbel distributions with mean 0 and variance $\pi^2/6$ and that these are independent and homoscedastic [25].

$$P_{iq} = \frac{e^{Viq}}{\sum_k e^{Vik}} \quad (3)$$

In this study, an advanced modeling solution, known as the mixed logit model, is used to investigate the respondents' heterogeneity, assuming that selected distance coefficients follow normal random distributions across decision-makers, with the specific modes and theoretical justification provided in Section 4.2. This model is widely used to analyze how the same factors can differently affect several decision-makers [26]. Assuming that f is the probability density function of the β_{ij} parameters, and α_{ijz} are the z parameters defining f, the $\widetilde{P_{iq}}$ probability that a q decision-maker chooses i alternative has the formulation shown in Eq. 4 [27].

$$\widetilde{P_{iq}} = \int \frac{e^{Viq}}{\sum_k e^{Vik}} f(\beta|\alpha_{ijz}) d\beta_{ij} \quad (4)$$

Eq. (4) has no closed-form solution and was therefore evaluated numerically. The integral was approximated using 20-point Gauss–Hermite quadrature, which is well suited to normally distributed random parameters and provides a deterministic approximation to the integral. The approximated probability $\widetilde{\widetilde{(P_{iq})}}$ is given in Eq. 5.

$$\widetilde{\widetilde{P_{iq}}} = \sum_{r=1}^{R} \omega_r P_{iq} \beta_r \quad (5)$$

Where β_r are the parameter vectors evaluated at the quadrature nodes and ω_r are the corresponding quadrature weights. Eq. 5 was used to build a L likelihood function to estimate all the α_{ijz} unknown parameters as shown in Eq. 6.

$$L = \prod_{q=1}^{Q} \sum_i^{Iq} y_{iq} \cdot \widetilde{\widetilde{P_{iq}}} \quad (6)$$

Where y_{iq} is equal to 1 if the q decision maker selects i alternative (i = 1, ….., I_q), otherwise 0. There are a lot of techniques available in the literature to solve the likelihood maximization problem to estimate the values of α_{ijz} which maximizes this function.

The results from the classic multinomial logit model and mixed logit model are also compared in this study. This comparison is performed using two methods as follows:

1. Comparing the fitting metrics such as the Log-likelihood values (LL) and the McFadden R^2. [28] Since these two models are nested, it is possible to run this comparison using the Likelihood Ratio Test. This compares the goodness of fit of two competing statistical models based on the ratio of their likelihoods.
2. Comparing the distance elasticities of the two models by using the direct point elasticity proposed by Louviere et al. [29] in Eq. 7.

$$E_{X_{iqj}}^{P_i} = -\beta_{ij} X_{iqj}(1 - P_{iq}) \quad (7)$$

As such, it is possible to calculate the elasticities for each decision-maker. The probability-weighted sample enumeration method is used, as shown in Eq. 8, to calculate sample elasticities, being the more Impeccable approach among others [29].

$$E_{X_{iqj}}^{P_i} = (\sum_{q=1}^{Q} \hat{P}iq E_{X_{iqj}}^{P_{iq}}) / \sum_{q=1}^{Q} \hat{P}iq \quad (8)$$

Where P_i is the aggregate probability of choice of alternative i and $\hat{P}_{iq}$ is an estimated choice probability.

4. Results

4.1. Descriptive analysis

Table 1 presents a summary of the survey responses (n = 823). Approximately 60.6% of respondents are male, and 39.4% are female. Secondary-level students constitute the largest education group (34.4%), followed by university students (25.4%), higher secondary students (19.0 %), primary students (11.3%), and madrasah students (10.0%). Most households belonged to lower-income groups, with 34.1% in the low-income category and 39.5% in the lower-middle-income category, while only 10.9% were in the high-income category. Car ownership is low (9.4%), while 26.0 % of households own at least one motorcycle. The distribution of travel modes reveals that auto is the most frequently used mode (34.5%), followed by rickshaw (19.7%), local bus (13.1%), walking (11.3%), school bus/van (9.2%), CNG/tempo (4.9%), car (3.6%), and motorcycle (3.6%). This modal share reflects the distinctive transport ecology of Narayanganj, in which informal para-transit modes such as auto, CNG/tempo, and rickshaw collectively account for approximately 59% of all observed educational trips.

Table 2 presents the summary statistics for the continuous variables, i.e., home-to-institution distance, one-way travel cost, travel time, and student age. The mean home-to-institution distance is 3.98 km (SD = 4.53 km), with a wide range from 0.14 to 36.24 km. The mean one-way travel cost is BDT 30.68 (SD = 59.13), and the mean travel time is 18.69 min (SD = 15.15 min), with a range of 1 to 150 min, reflecting congestion in Narayanganj city during morning peak hours. The mean student age was 16.26 years (SD = 4.89 years), ranging from 5 to 30 years.

Table 2 Summary of continuous variables

Variable	Mean	SD	Min	P25	Median	P75	Max
Home-to-institution distance (km)	3.98	4.53	0.14	1.64	2.47	4.14	36.24
One-way travel cost (BDT)	30.68	59.13	0.00	10.00	20.00	30.00	550.00
One-way travel time (min)	18.69	15.15	1.00	10.00	15.00	20.00	150.00
Student age (years)	16.26	4.89	5.00	13.00	16.00	20.00	30.00

Note: BDT = Bangladeshi Taka. 1 USD ≈ BDT 110 (approximate survey period rate).

Mode-specific summaries of distance, cost, and travel time are presented in Table 3. Walking is associated with the shortest distances (mean 0.73 ± 0.24 km) and zero cost, as expected. Rickshaw trips are also short (mean 1.92 ± 0.79 km), while motorcycles (mean 12.20 ± 6.09 km), local buses (mean 8.77 ± 5.55 km), and cars (mean 9.71 ± 7.79 km) serve considerably

longer distances. Car is by far the most expensive mode (mean BDT 201.00), followed by motorcycle (BDT 87.17), while auto (BDT 15.84) and school bus/van (BDT 17.08) are the cheapest motorized options. Boxplots of travel distances and travel distances for different modes, shown in Fig. 2, also depict the same picture.

Table 3 Mode-specific travel characteristics

Mode	n	Distance mean ± SD (km)	Cost mean ± SD (BDT)	Time mean (min)	Age mean ± SD (yr)
Auto	284	2.55 ± 1.08	15.84 ± 9.84	13.72	16.78 ± 4.21
Local bus	108	8.77 ± 5.55	47.90 ± 93.33	35.65	19.94 ± 3.17
Car	30	9.71 ± 7.79	201.00 ± 125.32	32.17	16.73 ± 4.38
CNG/Tempo	40	4.74 ± 4.74	46.25 ± 62.62	22.88	19.68 ± 3.33
Motorcycle	30	12.20 ± 6.09	87.17 ± 54.81	35.67	21.07 ± 4.94
Rickshaw	162	1.92 ± 0.79	23.38 ± 9.77	14.20	15.08 ± 4.73
School bus/van	76	4.97 ± 4.58	17.08 ± 17.77	19.54	11.46 ± 3.88
Walking	93	0.73 ± 0.24	0.00 ± 0.00	9.68	13.19 ± 4.09

Non-parametric hypothesis tests assess whether these differences are statistically reliable, and the results are summarized in Table 4. The Kruskal-Wallis test assesses whether the central tendency of distance, cost, time, and age differed across the eight travel modes simultaneously. The Mann-Whitney U test is used for planned pairwise comparisons between male and female students and between selected pairs of modes with similar cost profiles. All four Kruskal-Wallis tests are highly significant ($p < 0.001$), confirming that distance, cost, travel time, and age differ systematically across the eight modes. This suggests systematic differences in observed travel conditions across modes and motivates their consideration in the subsequent choice analysis presented in Section 4.2.

Among the Mann-Whitney comparisons, the gender results are particularly informative. Home-to-institution distance does not differ significantly between male and female students ($U = 78{,}904$, $p = 0.561$), nor do travel time ($U = 77{,}501$, $p = 0.303$) or age ($U = 83{,}124$, $p = 0.492$). Travel cost, however, is significantly higher for female students (mean BDT 36.79) than for male students (mean BDT 26.72; $U = 74{,}333$, $p = 0.047$). Because distance is statistically equal between genders, this cost difference is not explained by travel distance. It is consistent with gender differences in the feasible set of modes, and distance is analyzed further in Section 4.1.2.

Among the mode-pair cost comparisons, auto and school bus/van are not significantly different in cost ($U = 11{,}034$, $p = 0.753$), despite serving very different service models. Auto is an informal point-to-point hire-based mode. School bus/van is a contracted, supervised service. Rickshaw is significantly more expensive than auto ($U = 11{,}162$, $p < 0.001$). It is also significantly more expensive than school bus/van ($U = 7{,}704$, $p = 0.001$), despite serving much shorter distances on average than either mode. Car is, unsurprisingly, significantly more expensive than auto ($U = 8{,}422$, $p < 0.001$). Local bus and rickshaw costs are not significantly different from one another ($U = 7{,}946$, $p = 0.185$), despite the large difference in their mean values.

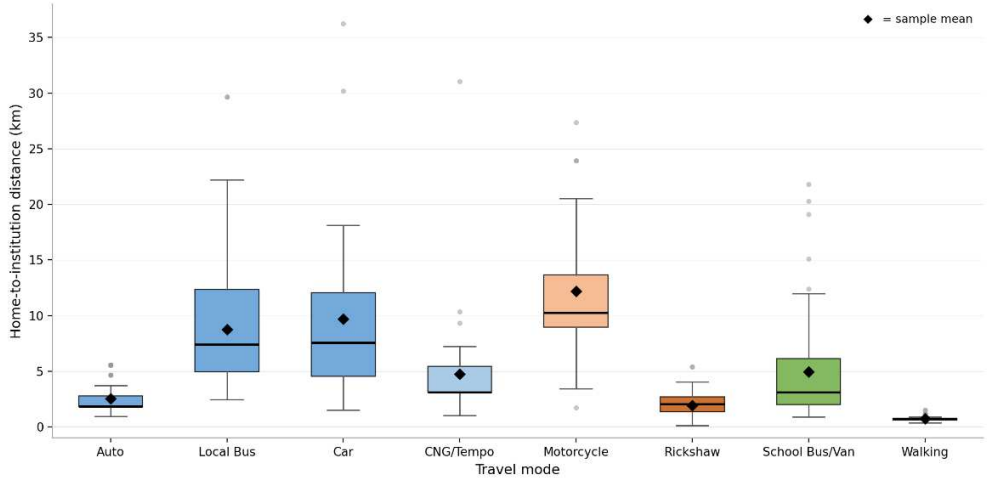


Fig. 1. Boxplot of one-way travel distance (home to institution) for each mode

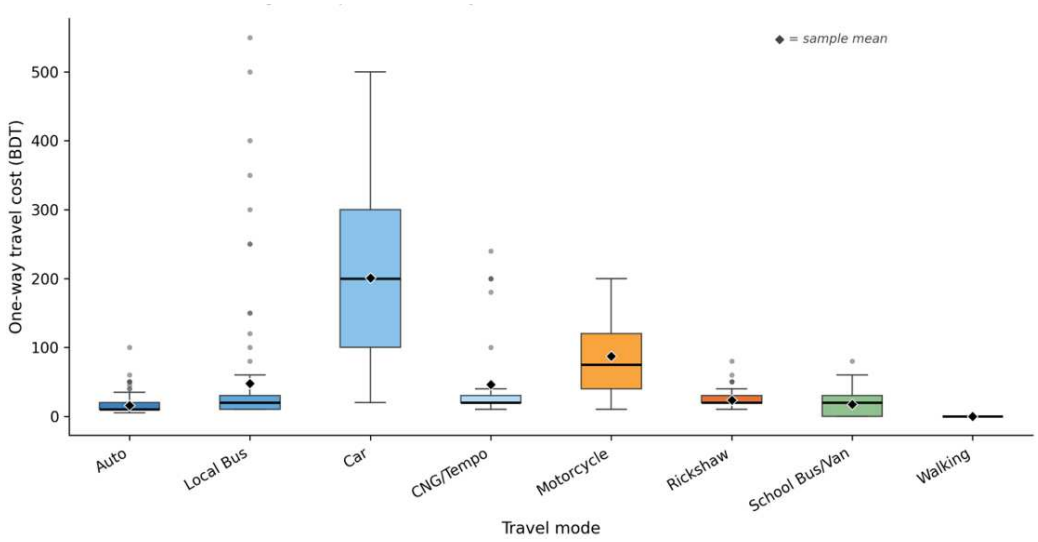


Fig. 2. Boxplot of one-way travel cost (home to institution) for each mode

Table 4 Summary of Kruskal-Wallis and Mann-Whitney U test results

Variable	Comparison	Statistic	p-value	Sig.
Kruskal-Wallis H test (across all 8 modes)				
Distance (km)	All 8 modes	516.110	< 0.001	***
Cost (BDT)	All 8 modes	407.228	< 0.001	***
Time (min)	All 8 modes	303.017	< 0.001	***
Age (years)	All 8 modes	229.583	< 0.001	***
Mann-Whitney U test (pairwise comparisons)				
Distance (km)	Male vs Female	78,904	0.561	n.s.
Cost (BDT)	Male vs Female	74,333	0.047	*
Time (min)	Male vs Female	77,501	0.303	n.s.
Age (years)	Male vs Female	83,124	0.492	n.s.
Cost (BDT)	Auto vs Rickshaw	11,162	< 0.001	***
Cost (BDT)	Auto vs School Bus/Van	11,034	0.753	n.s.

Variable	Comparison	Statistic	p-value	Sig.
Cost (BDT)	Rickshaw vs School Bus/Van	7,704	0.001	**
Cost (BDT)	Car vs Auto	8,422	< 0.001	***
Cost (BDT)	Local Bus vs Rickshaw	7,946	0.185	n.s.

*Note: Significance: *** p < 0.001, ** p < 0.01, * p < 0.05, n.s. = not significant. Kruskal-Wallis df = 7 throughout. Mann-Whitney U tests are two-sided.*

4.1.1 Modal share by age group

The modal share by age group shown in Fig. 3 demonstrates that among the youngest group, school bus/van (30%) and rickshaw (29%) together account for nearly 60% of trips, while local buses are essentially unused and walking is comparatively common (24%). Auto use is correspondingly low at this stage (15%), suggesting that for the youngest children, parents favor either a directly supervised, contracted service (school bus/van) or short, walkable, or rickshaw-assisted trips over independently used motorized transport. A notable transition is observed with the increase of age: auto use nearly triples to 39%, while school bus/van use falls sharply to 9%, and walking declines from 24% to 16%. Local bus use, although still marginal (1.6%), appears for the first time. With another increase in age, auto remains the dominant mode (39%), while school bus/van continues its decline (8%) and local bus use grows further (10%). The most pronounced shift occurs among the 18+ group, where local buses rise sharply to become the second most common mode (24%), school bus/van falls to only 1.4% of trips, and walking falls to its lowest share across any age group (5%). Motorcycles and CNG/tempo, both negligible among younger students, also reach their highest shares in this group (6% and 8%, respectively), consistent with the greater financial and physical independence of older students. Rickshaw use decreases with age but persists across all four groups, falling from 29% among the youngest students to 15% among the oldest, indicating its appeal to both independent older students and young dependent students who depend on this mode for their daily trips to educational institutions.

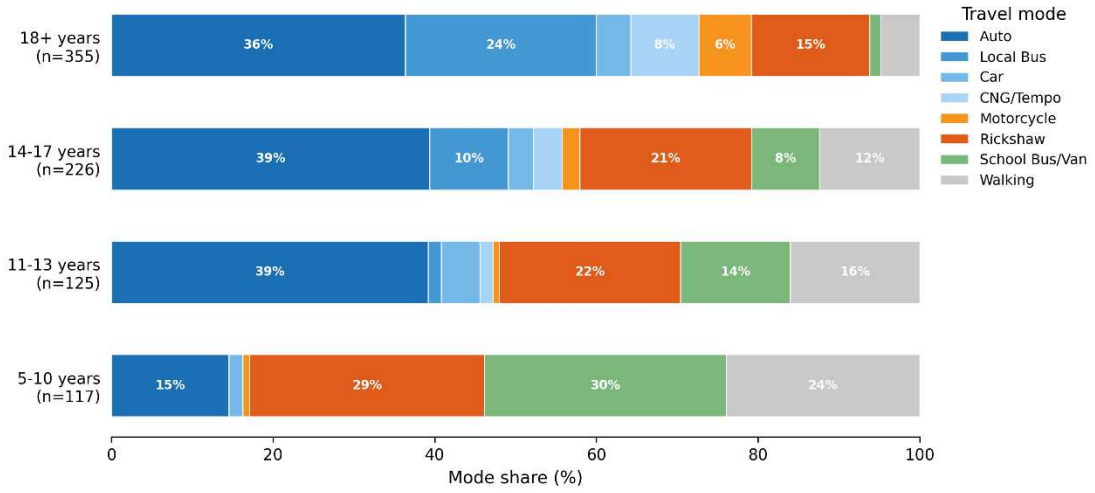


Fig. 3. Mode share by age group

4.1.2. Modal share by gender

The modal share by gender shown in Fig. 4 depicts that female students show a higher inclination for rickshaw and school bus/van use, while male students are more likely to use motorcycles and local buses. Motorcycle use is almost exclusively male. The Mann-Whitney U test shows that travel cost differs significantly between male and female students (U = 74,333, p = 0.047), while travel distance does not (U = 78,904, p = 0.561). This indicates that gender differences in mode choice are associated with the modes students use rather than with differences in home-to-institution distance. The higher relative use of rickshaws and school

vans by female students likely reflects greater perceived safety compared to open-seating public transport modes, where harassment is an alarming concern for women [30].

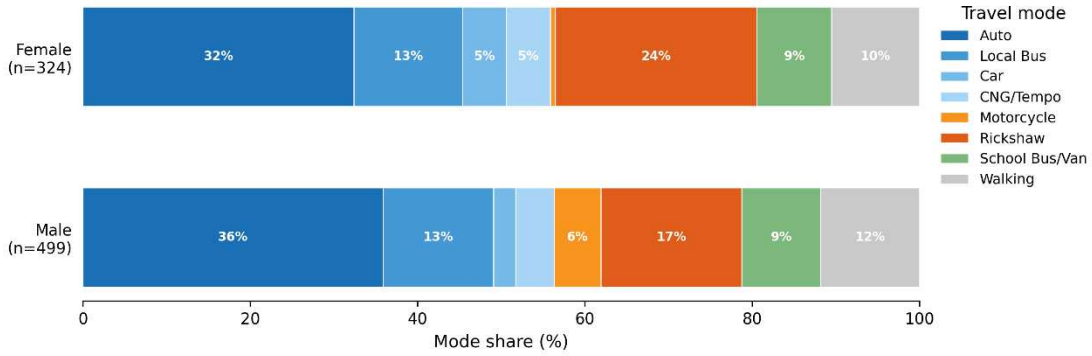


Fig. 4. Mode share by gender

4.1.3. Modal share by education level

Fig. 5 shows the mode share by education level. Among primary-level students, school bus/van (32.3 %) and rickshaw (29.0 %) together comprise the majority of trips, reflecting dependence on supervised or contracted transport at younger ages. At the secondary level, auto becomes the dominant mode (42.0 %). Local bus use rises sharply with educational progression, from negligible use at primary and madrasah levels to 30.1 % among university-level students, while school bus/van use falls to just 1.0 % at the university level. This is consistent with the expectation that older, more independent students shift away from contracted or supervised transport to shared public transport.

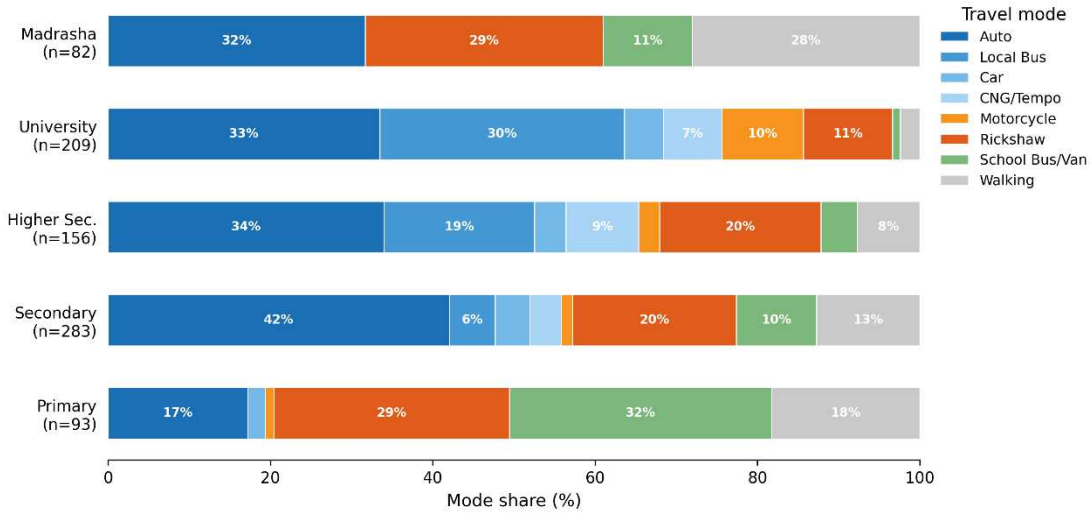


Fig. 5. Mode choice by education level

4.1.4. Influence of household income on educational trip mode choice

Fig. 6 shows mode share by household income group. With increasing income level, the share of auto declines significantly, from 45 % among low-income households to 11 % among high-income households, while car use rises correspondingly, from 0% to 19 %. Walking share also declines with income, from 8% among low-income households to 1% among high-income households. School bus/van use is highest among high-income households (17%), suggesting that higher-income parents are willing to pay for the safety and reliability associated with

organized school transport.

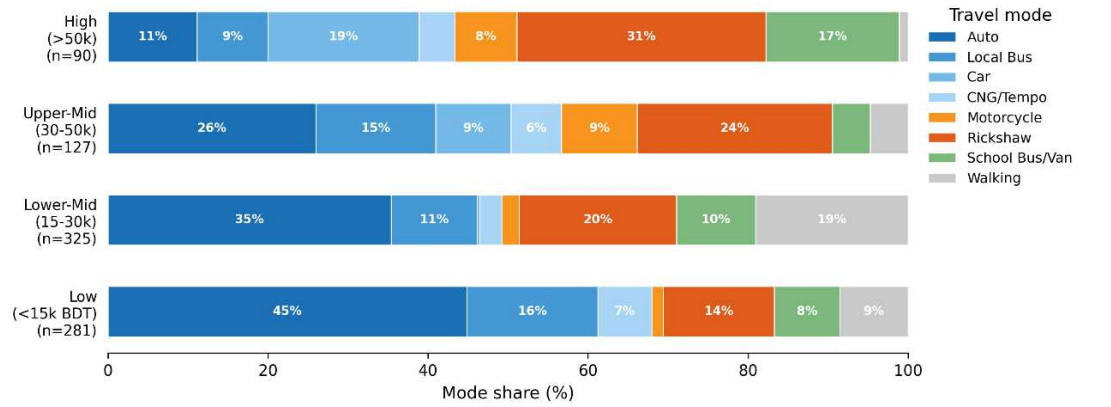


Fig. 6. Mode share by household income group (BDT/month)

4.2. Mode choice modelling

Discrete choice modeling is used in this study to investigate the factors influencing the mode choice of students going to different-level institutions. In this study, walking is used as the reference category, and six independent variables are taken: distance, gender, education level, household income, car ownership, and motorcycle ownership. Travel cost is excluded because it is endogenously determined by the mode chosen and the distance travelled, which is not an independent predictor. The correlations between independent variables were computed before estimating the model to avoid multicollinearity, and all Variance Inflation Factors (VIF) are below 1.50. Age was excluded from the model specification because education level directly and precisely captures the institutional progression relevant to school transport mode choice, and it is also a continuous proxy for this progression that adds no independent conceptual content. In this sample, age and education are moderately correlated ($r = 0.484$); education level was retained because the study focuses on educational-stage transitions, and age was excluded to avoid two overlapping representations of the same progression. Adding age alongside education yields a variance inflation factor of 1.477, indicating that the two are related but not interchangeable.

In the proposed mixed logit model, random parameters are restricted to the distance coefficients for Rickshaw and School Bus/Van only. This restriction is theoretically motivated: Rickshaw serves a mixed population in Narayanganj, where younger primary-level students are transported by parents, and older secondary and university students travel independently, generating heterogeneous distance sensitivity within the same mode. School Bus/Van is predominantly arranged by parents for younger children (39.5% primary-level, mean age 11.5 years), and household variation in willingness to travel to preferred institutions produces genuine dispersion in the distance coefficient for this mode [26], [31]. For all other modes: Auto, Local Bus, Car, CNG/Tempo, and Motorcycle, the distance coefficient is specified as fixed, as these modes are used predominantly by older independent students whose distance sensitivity is expected to be more homogeneous. Both models were estimated by maximum simulated likelihood using 20-point Gauss-Hermite quadrature and the L-BFGS-B algorithm [32]. Standard errors are computed using the Outer Product of Gradients (OPG) information matrix estimator ($B = \Sigma_i s_i s_i^T$), which replaces the diagonal Hessian approximation known to produce artificially deflated standard errors in maximum simulated likelihood models [26]. The full model specification is provided in Appendix A.

The estimated parameters for the multinomial logit and mixed logit models are presented in Table 5, with the fitting statistics provided in Table 6. The Likelihood Ratio Test confirms that the mixed logit with two random parameters fits the data significantly better than the MNL ($\chi^2(2) = 9.102$, $p = 0.011$). Both AIC (1837.88 vs 1842.98) and AICc (1844.76 vs 1849.32) favor the mixed logit. The McFadden R^2 improves from 0.490 to 0.493. The BIC marginally favors the MNL (2073.91 vs 2078.24), reflecting its heavier penalty for additional parameters; however,

since the two additional parameters (the random distance sigmas for Rickshaw and School Bus/Van) are theoretically justified and individually significant, the mixed logit is adopted as the preferred specification.

Table 5 Estimated Models: Multinomial Logit and Mixed Logit (reference mode: Walking)

Mode	Parameters	Est.	Std. Error	p-value	Sig.	Est.	Std. Error	p-value	Sig.
		Multinomial Logit Model				**Mixed Logit Model**			
Auto	ASC	-6.7276	1.0582	< 0.001	***	-7.0314	1.1081	< 0.001	***
	Distance (km)	7.6252	0.9380	< 0.001	***	7.7383	0.9931	< 0.001	***
	Female	-0.9054	0.6558	0.167		-0.9646	0.6608	0.144	
	Education	-0.2230	0.1844	0.227		-0.1599	0.1876	0.394	
	HH Income	-0.4386	0.4183	0.294		-0.4979	0.4330	0.250	
	Car Own.	1.0130	2.6579	0.703		0.8639	3.1770	0.786	
	Bike Own.	0.9099	0.6549	0.165		0.9073	0.6680	0.174	
	SIGMA_Dist	—	—	—	—	*Fixed (= 0)*			
Local Bus	ASC	-11.2528	1.2596	< 0.001	***	-12.0106	1.3700	< 0.001	***
	Distance (km)	8.5505	0.9458	< 0.001	***	8.7397	1.0025	< 0.001	***
	Female	-1.1274	0.7253	0.120		-1.2061	0.7408	0.104	
	Education	-0.2021	0.2603	0.438		-0.0448	0.2856	0.875	
	HH Income	-0.4855	0.4639	0.295		-0.6386	0.4855	0.188	
	Car Own.	0.6117	2.7185	0.822		0.5159	3.2276	0.873	
	Bike Own.	0.5845	0.7527	0.437		0.6187	0.7745	0.424	
	SIGMA_Dist	—	—	—	—	*Fixed (= 0)*			
Car	ASC	-13.8908	2.1594	< 0.001	***	-14.5380	2.2812	< 0.001	***
	Distance (km)	8.5456	0.9458	< 0.001	***	8.7215	1.0025	< 0.001	***
	Female	-0.3561	0.9036	0.694		-0.3719	0.9516	0.696	
	Education	-1.4163	0.3941	< 0.001	***	-1.3628	0.4275	0.001	**
	HH Income	0.8443	0.6573	0.199		0.7384	0.6812	0.278	
	Car Own.	3.4184	2.7756	0.218		3.5914	3.2818	0.274	
	Bike Own.	-0.4341	0.9634	0.652		-0.3515	1.0272	0.732	
	SIGMA_Dist	—	—	—	—	*Fixed (= 0)*			
CNG/Tempo	ASC	-10.8381	1.3840	< 0.001	***	-11.4175	1.4345	< 0.001	***
	Distance (km)	8.3105	0.9454	< 0.001	***	8.4735	1.0017	< 0.001	***
	Female	-0.8338	0.7538	0.269		-0.8963	0.7620	0.239	
	Education	-0.3370	0.2936	0.251		-0.2177	0.2998	0.468	

Mode	Parameters	Est.	Std. Error	p-value	Sig.	Est.	Std. Error	p-value	Sig.
		Multinomial Logit Model				**Mixed Logit Model**			
	HH Income	-0.3381	0.4908	0.491		-0.4440	0.5102	0.384	
	Car Own.	0.7886	2.7552	0.775		0.7390	3.2601	0.821	
	Bike Own.	1.0073	0.7791	0.196		1.0421	0.7960	0.190	
	SIGMA_Dist	—	—	—	—	*Fixed (= 0)*			
Motorcycle	ASC	-15.4462	1.8974	< 0.001	***	-16.5536	1.9849	< 0.001	***
	Distance (km)	8.6419	0.9472	< 0.001	***	8.8251	1.0040	< 0.001	***
	Female	-3.7070	1.2565	0.003	**	-3.6363	1.3035	0.005	**
	Education	-0.2481	0.4348	0.568		0.0104	0.4783	0.983	
	HH Income	0.0490	0.5328	0.927		-0.0922	0.5661	0.871	
	Car Own.	-0.4593	2.8210	0.871		-0.5218	3.3266	0.875	
	Bike Own.	3.2207	0.9584	< 0.001	***	3.2536	0.9702	< 0.001	***
	SIGMA_Dist	—	—	—	—	*Fixed (= 0)*			
Rickshaw	ASC	-7.0247	1.0259	< 0.001	***	-6.9704	1.0374	< 0.001	***
	Distance (km)	6.8585	0.9321	< 0.001	***	6.6025	0.9440	< 0.001	***
	Female	-0.4729	0.6682	0.479		-0.4780	0.6889	0.488	
	Education	-0.2695	0.1890	0.154		-0.2583	0.1946	0.184	
	HH Income	0.2850	0.4064	0.483		0.4019	0.4137	0.331	
	Car Own.	0.1935	2.6678	0.942		-0.2822	3.1744	0.929	
	Bike Own.	0.7583	0.6733	0.260		0.6825	0.6987	0.329	
	SIGMA_Dist	—	—	—	—	0.5191	0.2399	0.030	*
School Bus/Van	ASC	-8.6930	1.1191	< 0.001	***	-8.5619	1.1718	< 0.001	***
	Distance (km)	8.4667	0.9458	< 0.001	***	8.3702	1.0077	< 0.001	***
	Female	-1.0145	0.7092	0.153		-1.0064	0.7315	0.169	
	Education	-1.5214	0.2184	< 0.001	***	-1.5380	0.2278	< 0.001	***
	HH Income	0.2573	0.4367	0.556		0.3643	0.4504	0.419	
	Car Own.	-0.4238	2.6898	0.875		-1.1965	3.1399	0.703	
	Bike Own.	0.0594	0.7679	0.938		-0.0037	0.8057	0.996	
	SIGMA_Dist	—	—	—	—	0.2898	0.1230	0.018	*

*Note: All estimates from real survey data (n = 823). SE = OPG-corrected standard error. SIGMA_Dist = standard deviation of the random distance parameter; specified only for Rickshaw and School Bus/Van. All other modes: the distance coefficient is fixed (σ = 0). Significance: *** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.10. Reference mode: Walking.*

Table 6 Model fitting statistics

Statistic	MNL	ML
LL (null)	−1711.380	−1711.380
LL (final)	−872.489	−867.938
McFadden R^2	0.4902	0.4928
AIC	1842.98	1837.88
AICc	1849.32	1844.76
BIC	2073.91	2078.24
Estimated parameters	49	51
LRT $\chi^2(2)$	—	9.102
LRT p-value	—	0.011

Note: LRT compares ML vs MNL with df = 2 (two additional random parameters: σ_Rickshaw and σ_SchoolBus

Considering a significance level of 0.10, the following patterns appear from the mixed logit results.

Distance has a positive and highly significant effect ($p < 0.001$) on all seven non-reference modes in both models. The largest distance coefficients are observed for Motorcycle ($\beta = 8.825$), Local Bus ($\beta = 8.740$), and School Bus/Van ($\beta = 8.370$), and the smallest for Rickshaw ($\beta = 6.602$), consistent with the distance profiles in Table 3.

Because walking is the reference alternative, a positive distance coefficient means that increasing home-to-institution distance increases the probability of choosing the specified motorized mode relative to walking, holding other variables constant; it does not imply that longer trips increase the absolute use of any particular motorized mode.

Education level has a significant negative effect on Car ($\beta = -1.363$, $p = 0.001$) and School Bus/Van ($\beta = -1.538$, $p < 0.001$) in both models. Higher education level students are significantly less likely to use these modes relative to walking, reflecting that car and school bus/van users are predominantly younger primary-level students in this sample.

Gender has a significant effect on motorcycle use: female students are significantly less likely to use motorcycles relative to walking ($\beta = -3.636$, $p = 0.005$), consistent with motorcycle use being almost exclusively male. No other gender coefficients reach significance under OPG-corrected standard errors, though all Female coefficients are negative, indicating a general preference among female students for non-motorcycle modes.

Motorcycle/bicycle ownership has a positive and highly significant effect on Motorcycle use ($\beta = 3.254$, $p < 0.001$). Household income and car ownership do not reach conventional significance under OPG-corrected standard errors; the car ownership coefficient has particularly large standard errors due to near-complete separation between car mode users (87% car owners) and other mode users, which is acknowledged in the Limitations.

4.2.1. Random parameter results

The two random distance parameters are both individually significant: SIGMA_Dist for Rickshaw ($\sigma = 0.519$, $p = 0.030$) and for School Bus/Van ($\sigma = 0.290$, $p = 0.018$). Figure 7 illustrates their distributions alongside the five fixed-parameter modes.

For Rickshaw, the wider distribution ($\sigma = 0.519$) reflects the mode's mixed user base: it serves both younger primary-level students carried by parents who may travel longer distances for preferred institutions and older independent students who are more distance-constrained. For School Bus/Van, the significant sigma ($\sigma = 0.290$) reflects household-level variation in the willingness to send young children to more distant institutions, a decision driven by parental preferences for school quality rather than student preferences alone. For the five fixed-

parameter modes: Auto, Local Bus, Car, CNG/Tempo, and Motorcycle, the distance coefficient does not vary significantly across students, consistent with these modes being chosen independently by older students with relatively homogeneous distance sensitivity.

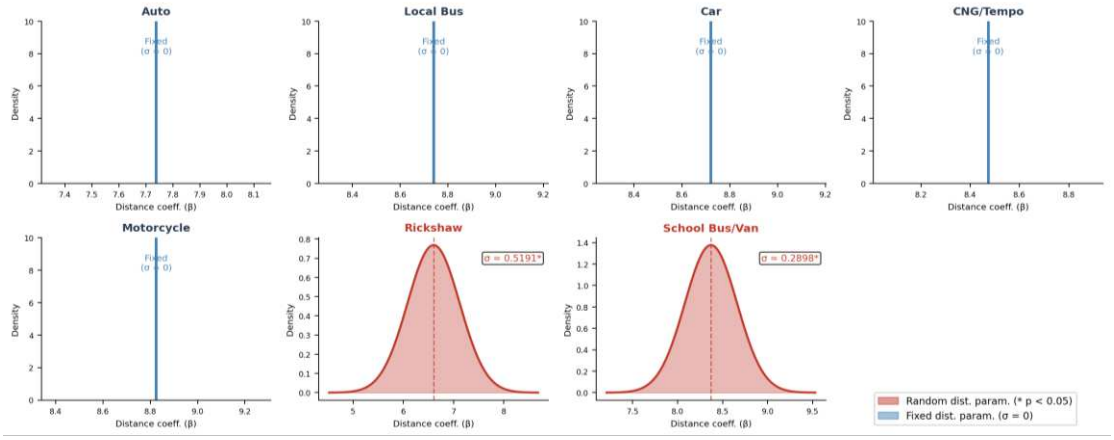


Fig. 7. Distribution of the distance coefficient by mode (mixed logit). Rickshaw and School Bus/Van display bell-shaped distributions reflecting significant unobserved heterogeneity in distance sensitivity (σ = 0.519, p = 0.030 and σ = 0.290, p = 0.018, respectively). All other modes have fixed distance parameters (σ = 0).

4.2.2 Gender differences in mode choice and travel-cost burden

A closer investigation of travel cost shows the differences in travel burden between male and female students. Since male and female students travel similar distances on average, differences in travel cost reflect the different transport modes they use rather than differences in trip length. Considering all trips with positive travel cost, the median cost per kilometer is significantly higher for female students than for male students (7.41 versus 5.85 BDT/km; Mann-Whitney U = 53,074, p = 0.034). When trips are disaggregated by distance, this difference is concentrated in the intermediate 2–5 km range (median 7.17 versus 6.44 BDT/km, p = 0.027), the distance band in which the choice between lower-cost shared modes and higher-cost enclosed or hired modes is most consequential. For very short and very long trips, the gender difference in cost per kilometer is not statistically significant.

This pattern is consistent with the mode-choice results. For short trips (0–2 km), walking and rickshaw remain practical options, and male and female students use similar combinations of transport modes and incur similar travel costs (median BDT 10 for both groups). Within the intermediate 2–5 km band, where the cost difference is concentrated, the composition of modes differs more substantially. Female students use rickshaws for 36.2% of trips in this band, compared with 20.0% among male students, while local buses account for 10.2% of female trips compared with 15.6% of male trips. This difference is consequential because rickshaws are among the most expensive modes per unit distance in this band (median 11.11 BDT/km), whereas local buses are the least expensive (median 3.04 BDT/km). The higher aggregate cost per kilometer among female students is therefore consistent with their greater dependence on hired, door-to-door rickshaw travel and comparatively lower use of public transport shared services at distances where both remain feasible.

4.3. Comparison of multinomial logit and mixed logit models

A comparison of the two models was carried out using the direct point distance elasticities of mode choice probabilities, calculated through the probability-weighted sample enumeration method [29]. These elasticities are shown in Table 7.

Table 7 Estimated elasticities of choice probabilities (MNL vs ML)

Mode	MNL Dist. Elasticity	ML Dist. Elasticity
Auto	-9.7878	-9.2945

Mode	MNL Dist. Elasticity	ML Dist. Elasticity
Local Bus	-35.0481	-31.6028
Car	-38.6305	-37.2035
CNG/Tempo	-35.4095	-36.0222
Motorcycle	-51.9987	-51.2149
Rickshaw	-8.5751	-7.6522
School Bus/Van	-29.4889	-20.6102
Walking	0.0000	0.0000

Note: All elasticities are probability-weighted sample averages from real survey data. A negative elasticity indicates that a 1% increase in home-to-institution distance reduces the probability of choosing that mode relative to walking.

The most significant difference between the two models is for School Bus/Van (MNL: −29.489; ML: −20.610), a reduction of approximately 30% in absolute value. This reflects the random distance parameter for this mode: the heterogeneity in distance sensitivity means that a subset of households remains relatively insensitive to distance when choosing a school bus/van, particularly those prioritizing institutional quality over proximity, thereby pulling the aggregate elasticity toward zero relative to the MNL's single fixed coefficient. This has direct policy implications: the MNL overstates the responsiveness of school bus/van demand to changes in home-to-institution distance, and the mixed logit provides a more flexible representation of distance responsiveness.

For Rickshaw, the ML elasticity (−7.652) is slightly smaller in absolute value than the MNL (−8.575), again reflecting heterogeneity: some households are insensitive to distance for this mode. For all other modes, Auto, Local Bus, Car, CNG/Tempo, and Motorcycle, the two models produce closely aligned elasticities, confirming that the fixed-parameter MNL is adequate. Motorcycles show the largest absolute distance elasticity (−51.998 under MNL, −51.215 under ML), consistent with this mode serving the longest mean trips (12.20 km) in the sample.

These values are choice-probability elasticities computed by probability-weighted sample enumeration: each figure gives the percentage change in the probability of choosing a given mode, relative to walking, for a one-percent change in home-to-institution distance, holding other attributes constant. Because the reference mode absorbs the complementary probability, the magnitudes are large and should be read as relative sensitivities across modes and models rather than as conventional market-demand elasticities.

5 Discussion

5.1 Informal transport as the foundation of educational mobility

The major finding of this study is the vital role of informal and intermediate transport in day-to-day educational transportation. Auto, rickshaw, and CNG/tempo together account for approximately 59% of observed educational trips. Rather than representing a marginal alternative to formal public transport, these modes form a major component of the daily connection between households and educational institutions in Narayanganj.

This is a significant finding from an urban planning perspective because it shows that a large portion of students are being served by modes other than traditional public transport. The demand created due to the lack of government-operated school bus services is accommodated through a combination of informal services, private vehicles, and institutionally arranged transport. This results in a transport system that creates challenges for regulation, safety, service quality, and accountability.

But if such a policy is adopted so that informal transport will be replaced by formal services immediately, it will be financially and operationally difficult in a rapidly growing secondary

city. A more practical approach would be to upgrade the conditions under which informal transport functions. Registration of operators, vehicle safety standards, designated pick-up and drop-off areas, and improved management of the operators would improve the informal transport services in the short-term period. For the medium-term and long-term period, the government should plan for dedicated educational bus services and improvement of public transport services throughout the city.

5.2 Educational progression as a mobility transition

The systematic differences in mode choice across educational stages provide evidence of a broader transition in educational mobility. Primary-level students are almost dependent on school bus/van and rickshaws, with a modal share of 32.3% and 29.0%, respectively. With the progress of age, the higher-class students increasingly use auto and local bus services. The modal share of buses rises from zero at the primary level to 5.7%, 18.6%, and 30.1% for secondary, higher secondary, and university students. The modal share of auto also shows the same picture, as it rises to 42%, 34%, and 33.5% at secondary, higher secondary, and university level. The walking trips also decreased, from 18.3% at primary level to 2.4% at university level, which supports the evidence that higher-level students travel longer distances that require motorized transport.

This pattern suggests a mode shift from more organized or household-arranged transport among younger students toward independently accessible modes among older students. At the primary level, as 61.3% of trips are carried out by rickshaws and school bus/van, designated pickup and drop-off arrangements through the city and institutions must be arranged for the school bus/van and for rickshaws; vehicle safety and driver licensing standards should be properly ensured. For the higher-level students, the route coverage of the public transport network along with the reliability and frequency should be ensured with proper financing, which is a medium- and long-term plan as stated in section 5.2. For the short-term period, the improvement of informal transport services would be appropriate.

5.3 Distance as a mechanism of spatial accessibility

Distance is one of the most consistent factors influencing the mode choice of students in the estimated models. Walking is mainly associated with short educational trips, with a mean distance of only 0.73 km, while the students who travel long distances use motorized transport modes. Motorcycle, local bus, and car users have especially long average travel distances. These patterns suggest that when the distance between home and institution increases, students get fewer opportunities to complete their journeys by active modes and become dependent on motorized transport.

These findings highlight the role of institutional location in shaping the transport burden of educational access. When institutions are located farther from residential areas, students have fewer opportunities to complete their journeys through active travel and become increasingly dependent on motorized transport. In Narayanganj, informal transport modes meet a significant portion of this additional demand. However, the estimated results do not suggest that the students stop walking and start using motorized transport at a fixed distance; instead, the changes occur gradually with the change in distance between home and institution. Hence, if new educational institutions are planned to be located farther from residential areas in the secondary cities experiencing rapid expansion without necessary improvements in active and public transport, it may increase the use of informal transport services. On the contrary, improving spatial accessibility of institutions might help reduce the demand for motorized modes.

This section also analyzes how modal share would differ if new educational institutions were located toward the urban periphery while keeping other factors unchanged. A 25% increase in home-to-institution distance in the estimated model would change the walking share from 11.3% to 7.5%, while the modal share of local bus and school bus/van rises by 3.4%and 2.6%, respectively. Notably, the combined share of informal three-wheeler paratransit (auto, rickshaw and CNG/tempo) does not increase; in fact, rickshaw loses share by 3.4%

because it primarily serves the short-distance trips, which become less attractive as distance grows. The findings of this section highlight the importance of considering the location of educational institutions in a city like Narayanganj, where public transportation services are limited.

5.4 Gender and mobility inequality

The gender results provide one of the clearest indications that educational mobility cannot be understood only through spatial distance. Male and female students travel statistically similar distances, yet female students incur significantly higher travel costs and are significantly less likely to use motorcycles. In the mixed logit model, the female coefficient for motorcycle is −3.636 ($p = 0.005$), and they also incur higher travel costs per kilometer, as discussed in Section 4.2.2. These results suggest a type of mobility where students with similar travel distance choose different modes of transportation and, as a result, incur different travel costs.

The plausible explanations for the differences could be safety perceptions, harassment experiences, or parental restrictions, but they should not be treated as established explanations, as the survey does not measure these factors. But similar conditions can be found in previous studies of educational travel conducted in South Asia [6,10–16]. From an urban planning perspective, this pattern shows that improving only spatial accessibility alone may not improve the observed scenario; improvements in safety, affordability, reliability, and social acceptability of the transport modes are also needed.

5.5 Household resources and transport access

The results shown in section 4.1.4 show that modal share differs significantly across different income groups. The modal share of auto decreases from 44.8% to 11.1% among low-income households to higher-income households, whereas car use increases from 0% to 18.9%. But these differences are not influenced by household income when distance, education level, gender, and vehicle ownership are considered.

Vehicle ownership shows a clearer relationship with specific mode choice. For example, motorcycle ownership is strongly associated with motorcycle use ($\beta = 3.254$, $p < 0.001$). This finding suggests that differences in educational mobility may be related not only to household income but also to whether students have ownership of a transport vehicle. In this perspective, vehicle ownership provides an important perspective for understanding differences in the transport options available to students.

5.6 Why heterogeneous distance sensitivity matters for urban planning

The mixed logit results also add an important dimension to interpreting educational accessibility. Significant heterogeneity in distance sensitivity is observed for rickshaws and school bus/van, with students using these modes not responding uniformly to changes in changing distances of home to the institution.

This finding is important because a standard mode-choice model represents distance sensitivity using a single average coefficient, which cannot portray differences among students. For example, elasticity of the school bus/van changes from −29.489 under the MNL to −20.610 under the mixed logit. The difference indicates that some students are much less distance-sensitive than the average student represented by the MNL coefficient. This behavior may represent differences in household preferences, institutional preferences, or transport arrangements, although these factors are not measured by the survey.

From an urban planning perspective, this means changes in the location of educational institutions or residential areas may not affect all students equally. Students who are more sensitive to distance may be more likely to change their transport mode or seek a closer institution, while others may choose to travel longer distances. Therefore, the transport impacts due to institutional relocation should be considered when models allow for differences in students' responses to travel distance.

Thus, the mixed logit model should be seen as a method of revealing variation in students' responses rather than simply as a statistically improved alternative to the MNL. Its main significance in this study is that it shows where a single average distance response may hide meaningful differences among students.

6. Conclusion

This study investigated home-to-institution travel mode choice among 823 students across primary, secondary, higher secondary, university, and madrasah education in Narayanganj, Bangladesh, using multinomial logit and mixed logit models. The following findings have been revealed by this study.

First, informal transport modes should be recognized as an important component of the city's accessibility system instead of treating them as a substitute for formal public transport, as auto, rickshaws, and CNG/tempo together account for approximately 59% of trips. Banning them in the city without improving the public transport system would cause a serious accessibility issue for the students; hence, measures such as operational regulation, vehicle safety standards, and designated pickup and drop-off stops could be established throughout the city. Second, the mode choice changes with the change in educational progression. Younger students depend more heavily on school bus/van and rickshaw services, whereas older students increasingly use shared public transport, particularly local buses. The significant negative associations between educational level and school bus/van use further support this transition. These results do not establish that educational progression directly causes greater travel independence, but they demonstrate that educational travel should not be treated as a homogeneous category across all student ages and institutional levels. Transport planning for different levels of students should therefore be considered differently within the same urban transport system. Third, differences in mode choice and travel costs are observed between male and female students traveling similar distances. Female students incur a significantly higher travel cost per kilometer and are less likely to use motorcycles. Therefore, improving the transport systems is needed in order to remove the observed gender differences so that all people can travel safely in all the existing modes. Fourth, distance sensitivity is not uniform across students. Significant heterogeneity is identified for rickshaw ($\sigma = 0.519$, $p = 0.030$) and school bus/van ($\sigma = 0.290$, $p = 0.018$), and the mixed logit provides a statistically better fit than the multinomial logit (LRT $\chi^2(2) = 9.102$, $p = 0.011$). The largest practical difference is observed for school bus/van, whose distance elasticity is approximately 30% smaller in absolute value under the mixed logit. This suggests that a single average distance response may overstate the sensitivity of school bus/van choice to change in home-to-institution distance.

Several limitations should be considered in these conclusions. First, the study uses a small number of private car and motorcycle users, with 30 users for each mode. This restricts the accuracy of mode-specific estimations. Second, the questionnaire did not measure the reasons behind the observed gender differences in mode choices, such as safety perceptions, harassment, or parental restrictions. In addition, the model does not include other factors that can affect transport accessibility, such as waiting time, service frequency, and service reliability. Future research should incorporate these limitations in their study.

Appendix A. Model specifications

This appendix provides the explicit model specification for the multinomial logit and mixed logit models proposed in Section 4.2. The mode coding used in the specification is: 1 = Auto; 2 = Local bus; 3 = Car; 4 = CNG/tempo; 5 = Motorcycle; 6 = Rickshaw; 7 = School bus/van; 8 = Walking (reference category). In the notation below, β denotes a fixed parameter and the corresponding variable is given in italics.

A.1. Multinomial logit specification

For each non-reference mode i (i = 1,…,7), the systematic utility relative to walking is specified as:

$$V_i = \beta_ASC_{,i} + \beta_Dist_{,i} \cdot Distance + \beta_Fem_{,i} \cdot Female + \beta_Edu_{,i} \cdot Education + \beta_Inc_{,i} \cdot HHIncome + \beta_Car_{,i} \cdot CarOwn + \beta_Bike_{,i} \cdot BikeOwn$$

with V_Walking = 0 (the reference alternative is normalised to zero utility). The choice probability for each mode follows Equation (3). This specification yields 7 × 7 = 49 estimated parameters (one alternative-specific constant and six slope coefficients per mode), as reported in Table 6.

A.2. Mixed logit specification

The mixed logit specification is identical to the MNL above for five modes (Auto, Local Bus, Car, CNG/Tempo, Motorcycle), where the distance coefficient is fixed across decision-makers. For Rickshaw (i = 6) and School Bus/Van (i = 7), the distance coefficient is allowed to vary across decision-makers according to a normal distribution:

For Rickshaw (i = 6):

$$\beta_Dist,6,q = \beta_Dist,6 + \sigma_6 \cdot \omega_q,6 \qquad \omega_q,6 \sim N(0,1)$$

For School Bus/Van (i = 7):

$$\beta_Dist,7,q = \beta_Dist,7 + \sigma_7 \cdot \omega_q,7 \qquad \omega_q,7 \sim N(0,1)$$

For all other modes (i = 1,…,5):

$$\beta_Dist_{,i},q = \beta_Dist_{,i} \qquad (\text{fixed}, \sigma_i = 0)$$

where σ_6 and σ_7 are the standard deviations of the random distance parameter for Rickshaw and School Bus/Van respectively (reported as SIGMA_Dist in Table 5), and ω_q,6, ω_q,7 are standard normal draws specific to decision-maker q. Substituting into the utility function:

For Rickshaw and School Bus/Van (i = 6,7):

$$V_\{i,q\} = \beta_ASC_{,i} + \beta_Dist_{,i},q \cdot Distance + \beta_Fem_{,i} \cdot Female + \beta_Edu_{,i} \cdot Education + \beta_Inc_{,i} \cdot HHIncome + \beta_Car_{,i} \cdot CarOwn + \beta_Bike_{,i} \cdot BikeOwn$$

For all other modes (i = 1,…,5):

$$V_\{i\} = \beta_ASC_{,i} + \beta_Dist_{,i} \cdot Distance + \beta_Fem_{,i} \cdot Female + \beta_Edu_{,i} \cdot Education + \beta_Inc_{,i} \cdot HHIncome + \beta_Car_{,i} \cdot CarOwn + \beta_Bike_{,i} \cdot BikeOwn$$

This specification adds two additional parameters (σ_6 and σ_7) to the 49 fixed parameters of the MNL, for a total of 51 estimated parameters, matching the count reported in Table 6.

A.3. Estimation procedure

Both models were estimated by maximum simulated likelihood in Python (NumPy/SciPy). The MNL log-likelihood (Eq. 3) was coded in closed form with an analytical gradient. The mixed logit log-likelihood (Eqs. 4–6) was approximated using 20-point Gauss-Hermite quadrature applied to the two random distance parameters; for the five fixed-parameter modes, the deterministic utility enters directly without numerical integration. The L-BFGS-B quasi-Newton algorithm (Byrd et al., 1995) was used for optimization with convergence criteria

on gradient norm and objective function change. Standard errors were computed using the OPG estimator: $B = \Sigma_i s_i s_i^T$, where $s_i = \partial \log P_i(\theta)/\partial\theta$ is the individual score vector. The variance–covariance matrix is $Var(\theta) = B^{-1}$, and standard errors are the square roots of the diagonal elements.

Data Availability

The datasets generated during and/analyzed during the current study are available from the corresponding author upon reasonable request.

Author contributions

Fahim Faisal: Conceptualization, Methodology, Formal analysis, Writing – original draft. Lubaena Masud: Formal analysis, Writing - Review & Editing. Nushrat Zahan Mim: Validation, Writing – original draft

Funding

The survey was conducted under the Comprehensive Transport Masterplan for Narayanganj City Corporation project. The research itself received no funding; it was done entirely on the authors' own initiative.

Declarations

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Claude to improve and correct the grammar and readability of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Clinical trial number

Not applicable.

Ethical Approval and accordance

This study involved survey-based primary data collected from the residents of the Narayanganj City Corporation (NCC). No clinical, biomedical, or invasive procedures were conducted. The study adhered to all relevant institutional, national, and international ethical guidelines for research involving human participants. The survey protocol was reviewed and approved by the Institutional Review Board (IRB) of Bangladesh University of Engineering and Technology (BUET) and Dhaka Transport Coordination Authority (DTCA), in accordance with the ethical principles and guidelines outlined in the Belmont Report: Ethical Principles and Guidelines for the Protection of Human Subjects of Research (1979).

Consent to Participate

Informed consent was obtained from all participants and from the parents in the case of children for participation in the study. Also, participation in this study was voluntary, and respondents had the choice to withdraw from the study at any time**.**

Consent to Publish

Informed consent was obtained from all the individual participants for publication in this study.

Competing interests

The authors declare no competing interests.

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