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ARE PARATRANSIT USERS REALLY DIFFERENT FROM ACTIVE MODE TRAVELERS FOR FIRST AND LAST MILE CONNECTIVITY: LESSON LEARNED FROM MRT USERS

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Abstract:

Dhaka's first mass rapid transit (MRT) system has marked a critical shift in the city's public transport landscape, aiming to provide high-capacity, and reliable mobility. However, the effectiveness of this transportation mode depends on seamless first and last mile (FLM) connectivity. This study examines whether paratransit users differ meaningfully from active mode travelers in FLM connectivity for MRT system where paratransit like rickshaw is predominant. Using 1,513 valid home-interview responses, the research applies Principal Component Analysis (PCA) to extract three latent constructs, i.e., Travel Utility Perception, Travel Time & Cost Impact, and Socio-Demographic Profile. Structural Equation Modeling (SEM) is used to assess distinct models for walking and rickshaw as FLM modes. The findings reveal that the behavioral factors influencing paratransit use are closely aligned with those of active transport users, implying that in compact urban settings, paratransit may function as a substitute for active travel, potentially due to the lack of adequate walking and cycling infrastructure. Two models are then combined, referring to active FLM modes to investigate how their trip making behavior interact with each other. Key findings indicate that trip distance, fare sensitivity, time savings, and socio-economic status significantly influence FLM mode choice. The combined model of active travel yielded the best fit (RMSEA = 0.102; CFI = 0.848; TLI = 0.875), suggesting rickshaws function as pragmatic extensions of active travel rather than discrete modes. These results emphasize a continuum-based strategy for FLM planning that integrates rickshaw-friendly and walkable infrastructure to maximize accessibility and inclusivity along MRT corridors in built-up areas.

Keywords: *paratransit, active mode travelers, first-last mile connectivity, structural equation modeling, MRT*

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1. Introduction

As urban populations continue to grow and cities expand horizontally at an unprecedented rate, the demand for efficient, sustainable, and inclusive transportation system becomes increasingly critical. In response to escalating traffic congestion, environmental degradation, and the rising need for daily mobility, many cities in developing countries have turned to mass rapid transit (MRT) systems as a transformative solution (Ali et al., 2025). However, the success of such systems extends beyond the construction of rail lines and stations depends on how accessible and convenient these systems are for the commuters they aim to serve. Also, attempts to boost rail usage typically concentrate on improving the rail service itself, with less emphasis on the accessibility of the rail network (Brons et al., 2009). A key determinant of this accessibility lies in the quality of first and last mile (FLM) connectivity, the initial and final legs of a commuter's journey that link their origin and destination to the fixed-route MRT network. In urban environments like Dhaka, where unplanned development, high density, and infrastructural deficiencies prevail, FLM connectivity emerges as a critical bottleneck to public transport utilization (Raihan et al., 2024). Without efficient, safe, and user-friendly FLM options, metro systems risk remaining under-utilized, regardless of their operational efficiency or coverage.

FLM travel is typically supported by active transport modes such as walking and cycling (Wismadi et al., 2025), as well as by various forms of paratransit, including both motorized and non-motorized services. The choice among these modes is influenced by a complex set of factors: service quality, physical infrastructure, safety and security conditions, environmental design, ease of payment, and broader socio-demographic characteristics of users (Tanwar et al., 2024). Importantly, these influencing factors are highly context dependent. In developed countries, robust pedestrian and cycling infrastructure, planned urban form, and integrated transport systems support a smoother first and last mile experience (Lu et al.,2024). In contrast, cities in developing countries face a host of challenges, including fragmented urban layouts, informal transit operations, and a lack of dedicated infrastructure, all of which profoundly affect user preferences and behavior (Peimani et al., 2022). While studies in developed countries have offered useful frameworks and modeling approaches, their direct application to a built-up city like Dhaka, a megacity in South Asia, may be inappropriate without proper contextual adaptation. This is particularly important because a large segment of the population here does not rely solely on walking or cycling for FLM travel. In fact, rickshaws account for nearly 32% of paratransit services in Dhaka (RSTP, 2015), highlighting the relevance of investigating differences between paratransit and active transport modes in this context.

Dhaka, the capital of Bangladesh, recently inaugurated its first metro rail line, MRT Line 6, in an effort to revolutionize its urban transport landscape. Historically dominated by slow, overcrowded, and low-cost public buses, Dhaka's transport choices were largely shaped by affordability rather than reliability or efficiency. The introduction of the MRT introduces a new dynamic, offering rapid and reliable service at a higher cost. This creates a distinct trade-off scenario where commuters must balance travel time savings against increased fares, all while contending with potentially inadequate access to and from the MRT stations (Mijares, 2014). In built-up environment like Dhaka, where paratransit like rickshaw is predominant because of heavy dependence on mobility (Batool et al., 2024), active modes, such as walking and bicycling for ensuring accessibility sometimes get replaced by this mode. In this study, the authors analyzed if predominant paratransit like rickshaw really represents active transportation. Furthermore, to the best of the author's knowledge, no prior research has specifically examined the potential replacement of active transport with paratransit within built-up environments for FLM connectivity. Given that paratransit modes dominate in such settings, it is crucial to identify potential contrasts with active modes of transportation. Therefore, this study seeks to investigate how users of Dhaka's MRT system perceive the importance of several FLM mode (walking, rickshaw) attributes, with particular emphasis on the influence of socio-demographic and trip-related factors on access and egress mode choices. In addition, this research highlights the significance of how trip making characteristics of active transport users interact with each other.

2. Literature review

The rapid horizontal expansion of urban areas, particularly metropolitan cities, has resulted in increased mobility demands among daily commuters (Zhao et al., 2010). The combination of high population growth, high employment density, and the tendency to reside within or near city centers has led to severe congestion in these urban cores. To mitigate congestion and optimize land use, developing countries have increasingly focused on the development of satellite townships (Krishnan et al., 2021). A sustainable urban mobility system requires minimizing the number of private vehicles on the road to reduce congestion and environmental impacts. Consequently, urban planners encourage the use of mass transit services while promoting paratransit modes to provide shared and demand-responsive transportation options.

However, mass transit typically operates on fixed routes with designated stops and hubs. To connect these stops with passengers' points of origin and destinations, First and Last Mile (FLM) connectivity is essential (Shaheen et al., 2016). In transportation, FLM connectivity refers to the initial and final segments of a journey made using either public or mass transit. The first mile denotes the trip from a commuter's starting point to the transit station, while the last mile covers the trip from the transit stop to the final destination. When accessibility to stations decreases due to poorly planned FLM connectivity, public transport systems, especially Mass Rapid Transit (MRT) networks experience a decline in ridership (Chakraborty et al., 2025). FLM connections in many developed cities are facilitated by active transportation modes, such as walking (Karesdotter et al., 2022) and cycling (Azimi et al., 2020; Wismadi et al., 2025), as well as paratransit services, which include both motorized and non-motorized options (Kar et al., 2022; Rahman et al., 2022).

Active transport, including walking and cycling, is particularly valued as it contributes positively to commuters' physical and mental health (Friel et al., 2024). The choice of FLM modes depends largely on the perceived importance of multiple attributes, such as service quality, infrastructure availability, safety, security, convenience, and payment integration. Additionally, variations in these perceptions are often linked to commuters' socio-demographic characteristics and trip attributes (Wei et al, 2019; Ji et al., 2017). For active transport, commonly emphasized factors include the availability of pedestrian infrastructure (Paydar et al., 2020; Chidambara et al., 2019), walking environment quality (Gupta et al., 2022; Hussin et al., 2021), safety from traffic, security attributes such as lighting and CCTV cameras (Wu et al. 2021; Ji et al., 2017), and the overall distance between the origin and transit station (Venter et al., 2020).

To promote sustainable transport modes, numerous studies have examined users' perceptions of attributes influencing mode choice behavior. For example, a study on Beijing railway users applied a multinomial logit (MNL) model analyzing station access behavior, revealing that income and vehicle ownership significantly affect access and egress mode choices (Zuo et al., 2020). Similarly, a railway accessibility index has been developed in the Netherlands by using a nested logit model to simultaneously analyze egress station choice and access mode selection (Chakour et al., 2014). Another research conducted in Oregon examined mode choice behavior of access trip along a commuter rail line connecting suburb-to-suburb (Puello et al., 2014), while an analysis of Bay Area travel survey data demonstrated that built environment characteristics strongly influence access and egress mode choices for transit stations (Moyano et al., 2018).

Inspite of all this research, relatively few studies have addressed the context of Southeast Asian developing countries, where transportation supply characteristics differ significantly, and informal modes such as rickshaws and other paratransit options play a crucial role in urban mobility (Wang et al., 2021; Goel et al., 2016; Jyotika et al., 2025). To understand travel pattern in these regions, a MNL model has been applied to analyze mode choice across Mexico's urban areas (Guerra et al, 2018; Harbering et al., 2020), finding out that new high-capacity transit investments often have localized effects, attracting riders primarily from local buses and minibuses. Moreover, educational trip mode choices in Abbottabad, Pakistan, has been modeled, identifying socio-demographic attributes such as- sex, age, household income, travel time, travel cost, and trip distance as significant factors influencing students' travel behavior (Lodhi et al., 2021). However, this study explores the research gap concerning whether there are meaningful differences between paratransit modes like rickshaws and active transportation modes such as walking, aiming to assess if paratransit is really different from active mode of transportation.

3. Methodology

3.1. Data collection

Four MRT stations for MRT line-6 of Dhaka were selected for the Home Interview Survey (HIS) considering a 1500 m buffer area namely: Pallabi, Kazipara, Bijoy Sharani, and Motijheel representing industrial-dominated, residential-dominated, institutional-dominated, and commercial-dominated mixed land use types respectively. Once a station was identified, the required sample size (0.5% of the population) was calculated using population density data.

3.2. Procedure

The research was conducted using Alchemer software to collect accurate data through in-home interviews due to the low propensity to respond to online surveys using a well-designed mode choice behavioral survey. The survey took two cycles: the first from March 15, 2024, to May 16, 2024, and the second from June 22, 2024, to June 26, 2024.

3.3. Participants

This study's total sample size comprised 2,175 participants, divided into a pre-test group and a main study group. Final usable data was obtained from 1,513 participants, meeting the criteria set for quality and completeness.

The methodological workflow outlines the systematic approach used to conduct the research, detailing each step. A diagram of methodological workflow is shown in Figure 1.

The study corridor for this research focuses on the operational MRT Line 6 in Dhaka. Initially, preliminary variables for the questionnaire survey are selected based on an extensive literature review and expert opinions. This is followed by a pilot survey to refine these variables for the final data collection. Once the questionnaire form is finalized, data is collected from four operational metro stations. Data preprocessing is then conducted to prepare the data for analysis. Subsequently, descriptive statistics are performed based on respondents' perceptions. Then Principal Component Analysis (PCA) was performed to reduce the dimensionality of the dataset and to group the correlated variables under latent constructs. Finally, structural equation modeling (SEM) was performed with the observed and latent constructs and fit indices were determined to evaluate goodness of fit. The models were evaluated to determine whether the variables could explain the model.

3.4. Questionnaire Survey Design

The survey gathered information on various socioeconomic factors such as age, gender, income, education, and occupation. Additionally, household details like size, income, and vehicle ownership were also recorded. The survey was conducted, and all the questions were mandatory. Individual characteristics (age, gender, household income, employment status, and educational attainment) fall under the first category of socio-demographic variables while the second area focuses on factors specific to the chosen mode of transport, encompassing variables such as waiting time, vehicle travel time, fare, distance to the final destination etc. The third category, contextual considerations, includes things like trip objectives, weather and travel time of the day. The next step is to collect a detailed travel diary from respondents where respondents were asked to provide information about their trips from home to workplace and from workplace to home.

3.5. Data Preprocessing

The study sampled 2,175 participants, split into a pre-test and main study group, to refine and validate survey methodologies. The pre-test group was utilized to refine survey instruments based on its outcomes, thereby improving the validity of the main study. Out of 196 participants, most of the participants provided feedback under supervision but all did not complete the survey, with only 25 successfully finishing it. These responses were used solely to improve the survey's design and participant engagement, leading to adjustments for the main study. In the refined methods, the survey time was reduced to a tolerable limit based on the experience in the pretest phase. A total of 1,979 participants were engaged, drastically reducing the dropout rate seen in the pre-test, of which 1,701 completed the survey, and 1,513 responses met the required quality standards. Active monitoring and follow-ups ensured data reliability and integrity.

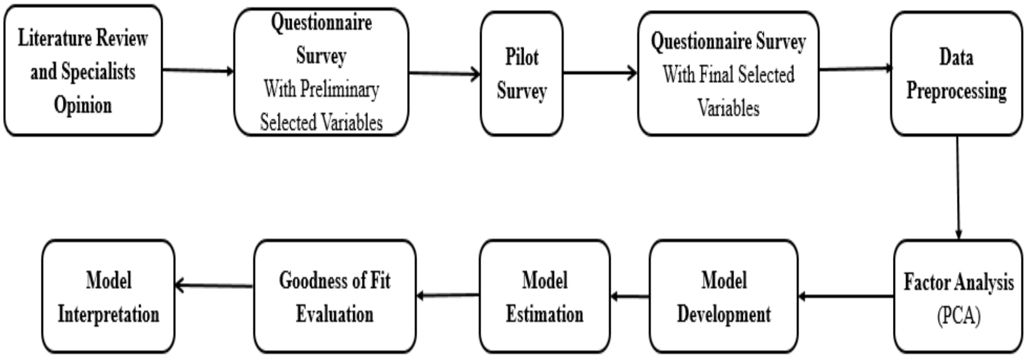

Fig. 1. Methodological Workflow

The dataset was prepared for analysis, ensuring it met the minimum required time of not less than 15 minutes for completion of survey, with 70.48% of the main study group providing usable data. This phased approach ensured a robust survey design and high-quality data collection.

3.6. Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) employs an iterative parameter estimation procedure that aims to achieve an optimal fit to the input data. The estimation process is based on covariance analysis, under the assumption that the population covariance matrix of the observed variables can be expressed as a function of unknown parameters (Ebadi et al., 2022). By estimating these parameters, SEM minimizes the discrepancy between the sample covariance matrix and the model-implied covariance matrix (Bollen, 1989).
SEM integrates two principal components including the measurement model and the structural model**.** A complete structural equation model comprises three sub-models consisting of two measurement models for endogenous (dependent) and exogenous (independent) variables, while another structural model that specifies the relationships among latent constructs. By combining principal component analysis (PCA) and path analysis, SEM effectively characterizes the relationships between observed indicators and underlying latent variables.

3.7. Descriptive Statistics of Respondents

The survey gathered information on various socio-economic factors such as age, gender, income, education, and occupation. Additionally, household details like size, income, and vehicle ownership were also recorded. Detailed travel behavior from the last working day was captured, including trip frequency, schedules, fares, waiting times, modes of transport, trip purposes, and activities during travel. Attitudinal questions gauged respondents' views on safety, convenience, affordability, inflation impacts, and family time which are shown in Table 1. After checking outliers, none of the features in the dataset contained null values. The survey was conducted using Alchemer software, and all the questions were mandatory.
According to mean, minimum and maximum values outliers were removed and for categorical data it was to ensure that it represents a normal distribution. Given the wide variation in values, the data was grouped into discrete bins and subsequently encoded for analysis. The average family income for both male and female MRT users (BDT 64,192) is lower than that of non-MRT users (BDT 75,686). This suggests that those using MRT have lower household incomes than those using non-MRT transportation modes.
Additionally, the overall trend indicates that, on average, males have higher personal incomes in both MRT and non-MRT modes than females. MRT users, regardless of whether they possess a Rapid Pass, generally experience shorter average access and egress travel times compared to non-MRT users, reflecting potentially superior accessibility and connectivity of MRT stations. Furthermore, the average age of MRT users appears similar between those with and without a Rapid Pass, which indicates that age has little influence on pass ownership. Individuals without private vehicles are more inclined to use

the MRT for somewhat longer distances, because it offers greater efficiency and convenience than other modes of transport. In contrast, non-MRT users who own private vehicles tend to cover slightly longer distances, suggesting a preference for private vehicles on longer trips.

Table 1. Summary of data collection

Variable Definition	Encoded Variable Names	Mean	Std	Min	Max
Level of Service Variables (Main Trip)					
Current Total Travel Time	TT Current Total	1.95	0.82	1	3
Travel Time of MRT Total	TT MRT Total	1.94	0.83	1	3
Current Total Fare	Fare Current total	1.88	0.83	1	3
Fare Difference between Bus and MRT	Diff Bus & MRT Fare	1.69	0.93	1	3
Time Savings by MRT compared to Bus	Saved Time by MRT Bus	1.99	0.81	1	3
Time Savings by MRT compared to Private vehicle	Saved Time by MRT PV	1.98	0.81	1	3
Total Waiting Time	Total Waiting Time	1.74	0.91	1	3
Classification For Short, Medium and Long Distance	Distance Class	1.78	0.8	1	3
Total Trip Distance	Total Trip Distance	2.0	0.81	1	3
Level of Service Variables (Access Egress Trip)					
Access Trip Distance in Kilometers	Total Distance for access trip	2.03	0.83	1	3
Access Egress Travel Time (min)	Access Egress TT	1.79	0.77	1	3
Access Egress Fare in BDT	Access Egress Fare	1.71	0.93	1	3
Destination within 500m of any MRT Station (1: Yes, 0: No)	Distance 500m	0.49	0.5	0	1
Attitudinal Variable					
Work-Centric Attitude during Commute	Work Centric	2.0	0.81	1	3
Inclination to Family	Family inclination	2.0	0.81	1	3
Perception of Pedestrian Infrastructure to the Transit Stop	Pedestrian Infrastructure	2.0	0.81	1	3
Reliability of the Preferred Mode	Reliability	2.0	0.81	1	3
Safety of the Preferred Mode	Safety	2.0	0.81	1	3
Flexibility of the Preferred Mode	Flexibility	0.23	0.42	0	1
Inflation of the Preferred Mode	Inflation	2.0	0.81	1	3
Walking as a Benefit	Walking Benefit	2.0	0.81	1	3
Technological Influence	Social media	2.0	0.81	1	3
Social Influence in Transport	Social influence	2.0	0.81	1	3
Socio-Economic Variables					
Age of the Respondents	Age	2.14	0.74	1	3
Sex of the Respondents (1: Male, 0: Female)	Sex (F=0)	0.66	0.47	0	1
Employment Status of the Respondents	Current Employment Status	2.42	0.76	1	3
Availability of Rapid/MRT Pass (1: Yes, 0: No)	Rapid pass/MRT pass for MRT (Y=1)	0.23	0.42	0	1
Highest Educational Degree	Last educational degree	2.31	0.73	1	3
Household Size	Household Size	2.1	0.78	1	3
No of Earning Family Members	Earning FM	1.62	0.67	1	3
Family Income	Family Income	2.13	0.7	1	3
Personal Income	Personal Income	1.74	0.77	1	3
Private Vehicle Ownership	PV Ownership	0.23	0.42	0	1

4. Results
4.1. Model Formulation
4.1.1. Factor Analysis
In the initial phase of model development, there were challenges of selecting a manageable yet meaningful subset of variables from an extensive list derived from literature, expert discussions, and pilot survey feedback. The broad range of attributes, compounded by varying definitions across studies, made this selection especially complex (Mahmuod et al., 2011).

To address this, Principal Component Analysis (PCA) was applied using STATA 13 to uncover latent patterns in the data and reduce dimensionality without losing critical information. PCA allowed us to group correlated variables into underlying latent constructs; unobserved concepts that explain shared variance among observed variables.

The number of retained components was determined using eigenvalues greater than 1 and scree plot analysis. According to Zaltman and Burger (1975), constructs with eigenvalues above 1 and cumulative explained variance exceeding 40% are considered meaningful (Zaltman et al., 1975). In our study, three latent constructs emerged, explaining a cumulative variance of 61.69%, comfortably above the suggested threshold.

These three constructs are:

– **L1: Travel Utility Perception** – Capturing how users perceive distance, fare differences, and time savings associated with MRT versus alternative modes.
– **L2: Travel Time & Cost Impact** – Focusing on access/egress time, total fare, waiting time, and related costs.
– **L3: Socio-Demographic Profile** – Including key personal characteristics like age, employment status, and income.

From an initial set of 33 observed variables, 12 variables were retained for inclusion in the Structural Equation Models (SEMs), guided by both statistical and theoretical considerations. Variables with factor loadings above 0.4 were prioritized, as they indicated a meaningful relationship with the underlying latent constructs (Hair et al., 2010). Although the initial pool included a broader range of indicators, several were excluded due to low factor loadings, suggesting weak associations with any conceptual factor. Others demonstrated significant cross-loadings, which created ambiguity in interpretation and could compromise model validity (Kline et al., 2016). Some variables were also found to be highly collinear with stronger indicators, offering little additional explanatory power. To enhance model parsimony and interpretability, we opted against including redundant or marginally relevant variables, in line with best practices in SEM (Byrne et al., 2016). Moreover, a few statistically acceptable variables were excluded based on expert judgment and contextual irrelevance, as they did not align well with the practical realities of FLM connectivity in Dhaka. This filtering process ensured the model remained focused on constructs with both experimental and contextual significance.

As a result, the final SEM structure focused on a theoretically sound, data-supported set of variables that best represented the behavioral dynamics of MRT users in Dhaka. This careful selection process ensured that our model not only fits the data well but also provides meaningful insights into how users perceive and experience FLM connectivity.

4.2. Model Development
To explore whether paratransit users meaningfully differ from active mode travelers in their FLM connectivity behavior, two structural equation models (SEMs) were developed: one where MRT users choose walking for FLM connectivity Figure 2 and another for those choosing rickshaw as FLM mode Figure 3. The models were estimated using 12 key variables categorized into three latent constructs: Travel Utility Perception (L1), Travel Time & Cost Impact (L2), and Socio-Demographic Profile (L3) which were previously mentioned in factor analysis section. These two models then further merged referring to FLM connectivity by active mode which is model 3 of this study Figure 4.

The three models exhibiting the inter-relationships of the latent components between (L1 and L2), (L1 and L3) and (L2 and L3) have been conducted, as expressed in Figure 2, Figure 3 and Figure 4.

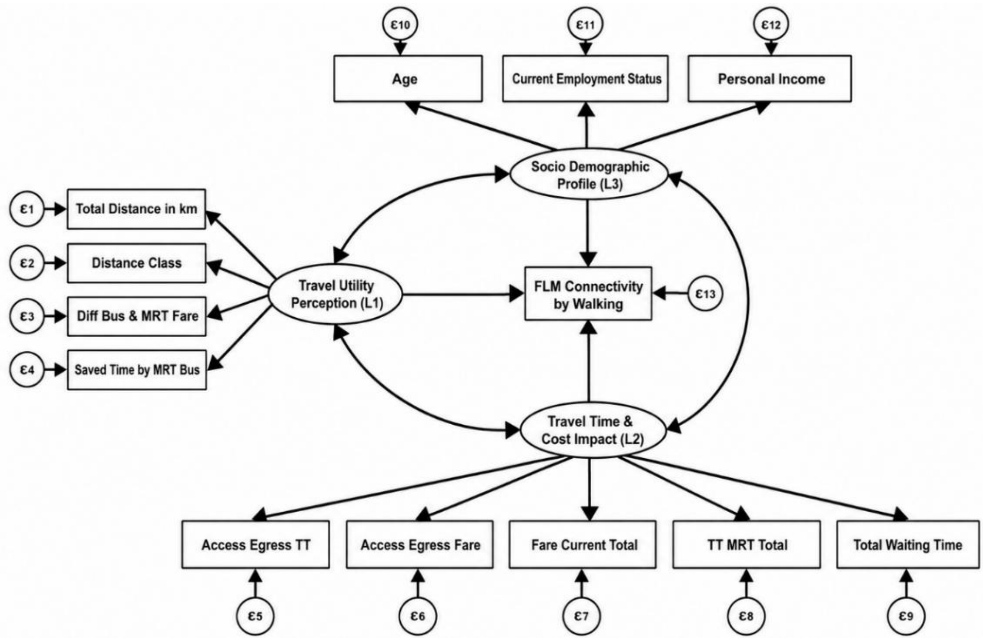

Fig. 2. Path diagram of FLM connectivity by walking (Model 1)

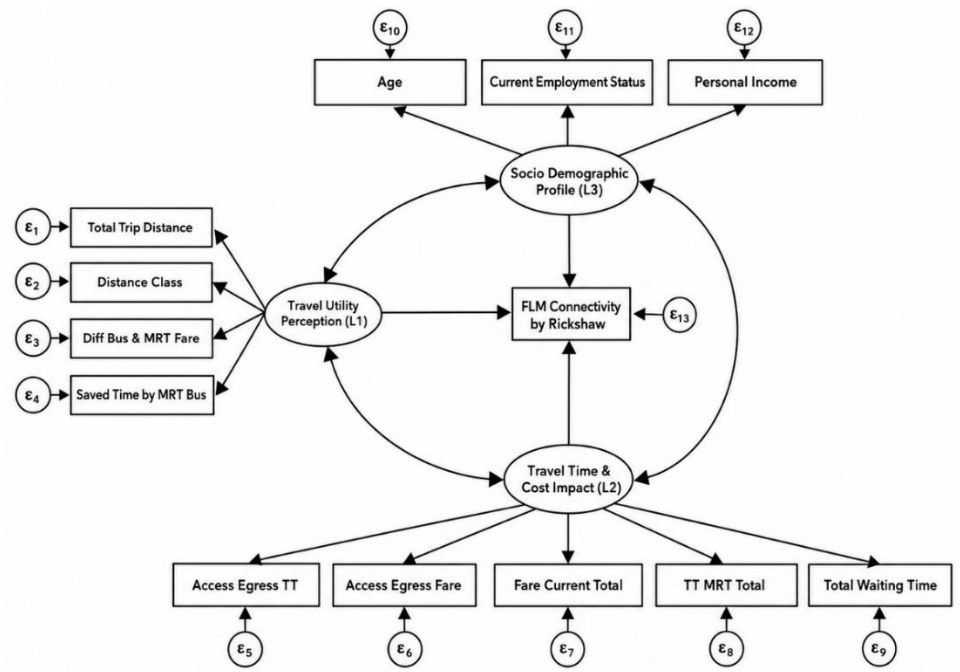

Fig. 3. Path diagram of FLM connectivity by rickshaw (Model 2)

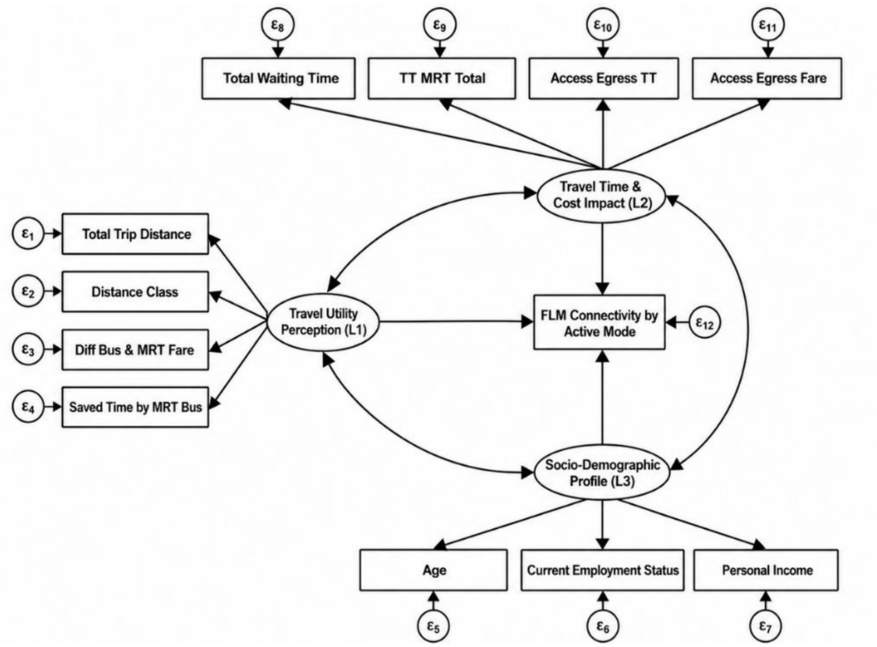

Fig. 4. Path diagram of FLM connectivity by active mode (Model 3)

4.3. Model Evaluation

To assess through data analysis whether paratransit (rickshaw) users exhibit different behavioral characteristics from active mode (walking) users in FLM connectivity, two structural equation models (Model 1: FLM Connectivity by Walking, Model 2: FLM Connectivity by Rickshaw) were developed. Both models were built on the same 12 observed variables grouped into three latent constructs: Travel Utility Perception (L1), Travel Time & Cost Impact (L2), and Socio-Demographic Profile (L3).

As shown in Table 2, both models produced statistically significant coefficients across all attributes, with p-values < 0.001 in every case. Under L1, attributes such as total trip distance, distance class, fare difference between bus and MRT, and time savings by MRT consistently showed high loading factors. For example, the total trip distance showed loadings of 0.894 in the walking model and 0.928 in the rickshaw model, suggesting that distance is a universally influential factor for all FLM users, regardless of mode.

Similarly, for L2, components like access/egress travel time, total fare, and waiting time retained strong explanatory power. Notably, access/egress fare had a higher loading in the rickshaw model (0.782) than in the walking model (0.493), indicating greater cost sensitivity among rickshaw users. This difference might reflect the monetary cost associated with paratransit compared to the no-cost nature of walking.

Socio-demographic characteristics under L3, particularly employment status and personal income also displayed strong and consistent influences across both models. For example, personal income had loading values of 0.886 and 0.958 for the walking and rickshaw models respectively, suggesting that income plays a substantial role in shaping FLM mode choice.

In Model 1, latent constructs L2 and L3 show strong correlations with L1 but are not significantly correlated with each other. In contrast, Model 2 reveals no correlation of latent construct L2 with L1 and L3, though the covariances between (L1, L3) and (L2, L3) remain consistently similar regarding significance across both model 1 and model 2. So, these two models are interpretable in almost similar way. Table 2 also presents the factor loadings, z-values, and significance levels for the three latent constructs in relation to the target variable. The results indicate that all three constructs have a direct and positive influence on the target outcome.

However, despite some variations in coefficient magnitudes, the overall structure and statistical significance of both models were remarkably similar. The strength and consistency of loadings across all variables indicate that, in Dhaka's built-up urban environment, the behavioral determinants of using paratransit are not substantially different from those of active transport users. This convergence suggests that rickshaw usage is functionally substituting for active mode of transportation in many FLM scenarios, especially in a context where walking and bicycling infrastructure may be lacking or time constraints dominate user decisions.

These results align with the study's objective to explore whether rickshaw users should be considered behaviorally distinct from active travelers. From the SEM model analysis, the evidence does not support significant divergence. Rather, in this context, paratransit appears to complement or replace active modes while responding to the same underlying factors such as travel distance, fare sensitivity, and user income underscoring its role as a pragmatic mobility solution in Dhaka's complex urban fabric. Therefore, it can be concluded that in the context of the built environment, where paratransit options like rickshaws play a critical role in ensuring FLM connectivity, active transport modes such as walking or cycling are often replaced by paratransit. In other words, in this context of developing countries, paratransit serves as a substitute for active transportation modes.

To further substantiate our findings and verify the consistency of behavior across access modes, a third structural equation model was developed merging the MRT users' data who relied solely on walking or rickshaw for their FLM trips, referred to as Figure 4: Active Mode. This model provides a holistic perspective by integrating all active travelers, thereby strengthening comprehensive analysis.

As shown in Table 3, the factors in Model 3 again mirror the patterns observed in the previous two models (Walking and Rickshaw). The model produced statistically significant coefficients across all attributes, with p-values < 0.001. Under the Travel Utility Perception (L1) construct, distance-related variables and fare/time trade-offs emerged as highly significant.

Table 2. Estimated parameters' values of FLM connectivity by walking and rickshaw model

Latent Construct	Attribute Parameters	**FLM Connectivity by Walking (Model 1)**			**FLM Connectivity by Rickshaw (Model 2)**		
		Coefficients	**z-value**	**p-value**	**Coefficients**	**z-value**	**p-value**
Travel Utility Perception (L1)	Total Trip Distance	0.894[a]	60.69	0.000	0.928	155.16	0.000
	Distance Class	0.9[a]	63.05	0.000	0.934	160.39	0.000
	Difference between Bus and MRT Fare	0.779[a]	49.68	0.000	0.749	60.65	0.000
	Time saving by MRT compared to Bus	0.612[a]	34.51	0.000	0.613	35.87	0.000
Travel Time and Cost Impact (L2)	Access or Egress Travel Time	0.782[b]	43.09	0.000	0.808	22.82	0.000
	Access or Egress Fare	0.493[b]	19.34	0.000	0.782	18.22	0.000
	Current Total Fare	0.429[b]	16.86	0.000	0.485	15.54	0.000
	Travel Time of MRT	0.795[b]	41.05	0.000	0.598	17.98	0.000
	Total Waiting Time	0.401[b]	15.58	0.000	0.429	17.03	0.000
Socio-Demographic Profile (L3)	Age	0.672[c]	18.1	0.000	0.619	16.38	0.000
	Current Employment Status	0.825[c]	19.03	0.000	0.902	17.46	0.000
	Personal Income	0.886[c]	18.21	0.000	0.958	17.14	0.000
	Latent Variables						
Co-variance	(L1, L2)	0.208	5.70	0.000	-0.025	-0.45	0.653
	(L1, L3)	0.279	9.93	0.001	0.249	8.65	0.000
	(L2, L3)	-0.006	-0.21	0.837	-0.049	-1.74	0.082
Factors with Target Variables	L1	0.319	10.72	0.000	0.224	7.65	0.000
	L2	0.096	3.38	0.001	0.339	12.55	0.000
	L3	0.096	3.35	0.001	0.119	13.04	0.000

Table 3. Estimated parameters' values of FLM connectivity by active mode

Latent Construct	Attribute Parameters	FLM Connectivity by Active Mode (Model 3)		
		Coefficients	**z-value**	**p-value**
Travel Utility Perception(L1)	Total Trip Distance	0.843[a]	50.1	0.000
	Distance Class	0.846[a]	52.32	0.000
	Difference between Bus and MRT Fare	0.83[a]	49.46	0.000
	Time saving by MRT compared to Bus	0.599[a]	29.34	0.000
Travel Time and Cost Impact (L2)	Access or Egress Travel Time	0.873[b]	37.27	0.000
	Access or Egress Fare	0.464[b]	20.02	0.000
	Travel Time of MRT	0.737[b]	32.79	0.000
	Total Waiting Time	0.401[b]	16.34	0.000
Socio-demographic Profile (L3)	Age	0.794[c]	47.34	0.000
	Current Employment Status	0.706[c]	39.92	0.000
	Personal Income	0.735[c]	40.98	0.000
	Latent Variables			
Co-variance	(L1, L2)	0.275	9.22	0.000
	(L1, L3)	0.088	2.02	0.003
	(L2, L3)	-0.066	-2.03	0.003
Factors with Target Variables	L1	0.480	18.29	0.000
	L2	0.000016	4.4	0.001
	L3	0.228	9.42	0.000

"a" indicates influence by Travel Utility Perception (L1)
"b" indicates influence by Travel Time & Cost Impact (L2)
"c" indicates influence by Socio-Demographic Profile (L3)

For instance, total trip distance and distance class showed coefficients of 0.843 and 0.846, respectively both with p-values < 0.001, demonstrating that users across all active modes consistently factor in physical distance when making access decisions. Similarly, the fare difference between MRT and bus and time savings by MRT retained strong influence, underscoring the importance of perceived value and efficiency in shaping behavior.

The Travel Time & Cost Impact (L2) construct revealed a particularly strong influence from access/egress travel time (0.873) and MRT travel time (0.737), highlighting users' sensitivity to total travel time and the cumulative burden of reaching and leaving the station. Interestingly, these values were slightly higher than those in the Rickshaw model, indicating that time is even more critical for users depending solely on their own physical effort.

Under the Socio-Demographic Profile (L3), age, employment status, and personal income once again showed consistent and strong influences, with coefficients ranging from 0.706 to 0.794. This affirms the idea that individual-level characteristics such as ability to work, earning potential, and age-related mobility preferences continue to shape FLM mode choices, regardless of whether the user is walking, cycling, or using paratransit. It is also seen from the loading factors mentioned in Table 3 that the three latent constructs have a positive and significant influence on target variables.

Crucially, Table 4 compares the goodness of fit indices for all three models. The RMSEA value for the active mode model was 0.102, notably lower than both the walking (0.144) and rickshaw (0.142) models, suggesting a better model fit. Similarly, CFI and TLI values were also highest for the active mode model (0.848 and 0.875, respectively), indicating a more robust representation of behavioral structure. Lower AIC and BIC values further validate the improved parsimony and explanatory power of Model 3.

Taking together, these results strongly support the central hypothesis of the study that paratransit and active transport users are not fundamentally different in how they perceive and respond to FLM travel demands. In Dhaka's dense, dynamic, and infrastructure-constrained urban settings, the choice between walking and rickshaw often depends more on practical trade-offs (like time and effort) than on distinct attitudinal or socio-economic profiles. Rickshaws, in many cases, act as an informal extension of active travel mode, serving those who would otherwise walk if the trip were shorter, safer, or less physically demanding.

Table 4. Goodness of fit measures

Fit statistics	FLM connectivity by walking (Model 1)	FLM connectivity by rickshaw (Model 2)	FLM connectivity by active mode (Model 3)
Absolute Fit Indices			
Root Mean Squared Error of Approximation (RMSEA)	0.144	0.142	0.102
Standardized Root Mean Square Residual (SRMR)	0.094	0.099	0.085
Co-efficient of Determination (CD)	0.999	1.001	0.995
Incremental Fit Indices			
Comparative Fit Index (CFI)	0.792	0.803	0.848
Tucker-Lewis Index (TLI)	0.720	0.730	0.875
Parsimony Fit Indices			
Akaike's Information Criterion (AIC)	38978.14	38174.417	35648.608
Bayesian Information Criterion (BIC)	39222.945	38424.544	35701.826

Thus, instead of drawing rigid boundaries between paratransit and active travel users, planners and policymakers should consider them as existing on a behavioral continuum one that reflects shared challenges and needs in achieving efficient and equitable MRT access where walking and bicycling infrastructure is insufficient and under-developed.

5. Discussion

Active travel, encompassing walking and cycling, is a relatively modern concept compared to older terms, and its boundaries often overlap and blur (Cook et al., 2022). Past research has highlighted the role of various paratransit modes, such as bicycles, rickshaws, and shared transport, in facilitating first and last-mile connections for public transport users (Kuijk et al., 2022). However, in the context of Dhaka's MRT, this study reveals a notable behavioral convergence between two modes. It has been evident that rickshaw users exhibit travel attitudes and constraints similar to those of pedestrians. Unlike traditional views that categorize paratransit and active travel as distinct modes, this research suggests that, in Dhaka, paratransit functions as an extension of active travel. It helps address gaps in infrastructure and spatial connectivity. In urban areas where proper pedestrian infrastructure is lacking, paratransit options like rickshaws and bicycles serve as functional substitutes for active modes of travel. This study contributes a novel perspective to existing literature, showing that the distinction between paratransit and active travel becomes less evident in densely populated, infrastructure-deficient environments, where paratransit supports the functionality of active travel.

6. Conclusions and policy implications

This study sets out to explore whether paratransit users specifically rickshaw users differ significantly from active mode users in their behavioral responses to first and last mile (FLM) connectivity challenges in the context of Dhaka's newly operational MRT system. Through the development of three structural equation models, we successfully addressed both core objectives of the research: (1) to determine whether paratransit users form a behaviorally distinct group from active travelers, and (2) to understand how users perceive and respond to key FLM attributes.

The SEM models revealed a high degree of similarity in the behavioral patterns of MRT users, whether they accessed the system by walking or by rickshaw. Across all three latent constructs, Travel Utility Perception, Travel Time & Cost Impact, and Socio-demographic Profile coefficients were consistently strong and statistically significant (all p-values < 0.001). For instance, total trip distance emerged as a dominant factor, with loadings ranging from 0.843 to 0.928 across the models, while income and employment status also showed robust influence (e.g., personal income loadings: 0.886 for walking, 0.958 for rickshaw). These findings suggest that users

across access modes respond to similar determinants, driven more by practical constraints than by fundamental behavioral differences.
Model 3, which combined all active modes, demonstrated the best overall model fit, with the lowest RMSEA (0.102) and highest CFI (0.848) and TLI (0.875), reinforcing the idea that rickshaw use in Dhaka functions as a pragmatic extension of active travel rather than a separate modal identity. This success in model performance not only validates the robustness of our analytical framework but also confirms our hypothesis that the behavioral distinction between paratransit and active travelers is minimal in this urban context. In the Travel Utility Perception construct of model 3, all the variables are consistently significant with the FLM connectivity by active mode, particularly trip distance related variables have the highest influence with loading factor 0.846 on active mode choice as user accessibility and mode choice depends on travel distance to the station. Similarly, Travel Time & Cost Impact, and Socio-demographic Profile coefficients are significant with loading factors ranging from 0.401 to 0.873, highlighting the extensive impact of trip making characteristics on active mode of transportation.
In achieving these outcomes, the study contributes critical insight to both academic literature and transport policy. While active transport and paratransit are typically viewed as distinct modes, in practice, users often switch between them when there's a substantial lacking of adequate, supportive, and dedicated infrastructure for active mode like walking or cycling, in the context of fragmented urban layouts. In such cases, paratransit serves as a practical substitute for active travel with influential factors, such as trip distance, time savings, and monetary costs of FLM mode. It emphasizes that in dense, infrastructure-deficient cities like Dhaka, planning efforts should move beyond binary categorizations of FLM users. Instead, a continuum-based approach acknowledging shared preferences and constraints is more appropriate for designing equitable, efficient multimodal transit integration.
The limitation of the study is that the analysis was confined to MRT Line 6 in Dhaka, and the findings may not be directly generalizable to other urban contexts with different land-use, transport, and socio-economic characteristics. Besides, the study focused solely on walking and rickshaw-based FLM connectivity, excluding other emerging feeder modes such as ride-sharing services, e-rickshaws, and bicycles. Future research may extend the proposed methodology to evaluate a broader range of FLM modes across diverse urban contexts. Nevertheless, the methodology is transferable to other developing cities where informal and paratransit services play a significant role in transit accessibility. The findings further suggest that integrating pedestrian infrastructure with rickshaw-supportive facilities can improve equitable MRT access and contribute to more inclusive and sustainable urban mobility systems.

Abbreviations

FLM-First and last mile
PCA-Principal Component Analysis
SEM-Structural Equation Modeling
RMSEA-Mean Squared Error of Approximation
SRMR-Standardized Root Mean Square Residual
CD-Co-efficient of Determination
CFI-Comparative Fit Index
TLI-Tucker-Lewis Index
AIC-Akaike's Information Criterion
BIC-Bayesian Information Criterion

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