

EVALUATING THE IMPACT OF USER PERCEPTIONS AND ATTITUDES: INSIGHTS FROM THE ADOPTION OF MRT LINE-6 IN DHAKA

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ABSTRACT

Metro rail systems play a pivotal role in alleviating traffic congestion and advancing sustainable mobility in rapidly urbanizing cities. Dhaka, one of Southeast Asia's most densely populated metropolitan areas, has recently introduced its first metro rail line, MRT Line-6, marking a transformative development in the city's transportation landscape. Beyond infrastructure and service quality, commuter perceptions and attitudinal factors substantially influence the adoption of new transit systems. This study investigates the role of attitudinal attributes in shaping the mode choice of MRT users. Data were collected through a revealed preference household survey conducted within a 1,500-meter buffer of nine operational MRT stations. The survey captured users' travel patterns, level of service experiences, and perceptions related to attitude. To determine the most influential attitudinal variables affecting mode choice Random Forest Gini Index and Analysis of Variance (ANOVA) score was used. Advanced machine learning techniques Random Forest (RF) and Support Vector Machine (SVM) were applied to analyze the data where RF emerging as the most suitable approach for model prediction and perceived results in capturing the complex, non-linear relationships between attitudes and mode adoption. Results revealed that attitudinal factors significantly enhance the predictive accuracy of mode choice models. Several key determinants of MRT usage using Shapley Additive (SHAP) were determined such as work-centric attitudes, safety perceptions, pedestrian friendly infrastructure, willingness to explore new technologies emerged as strong determinants of MRT usage, particularly among female and younger commuters. Additionally, attitudes toward flexibility and reliability of the service influenced the likelihood of shifting from private vehicle and bus to MRT. The findings highlight that incorporating attitudinal variables alongside other socio-demographic, level of service variables yields a clearer understanding of travel behavior, offering practical insights for transportation planners.

Keywords: *Attitudinal Attributes, Mode Choice, Machine Learning, SHAP, MRT*

1. INTRODUCTION

In many developing nations, rail-based transit systems particularly metro rail is increasingly regarded as a promising solution for promoting sustainable urban transportation and addressing critical challenges such as traffic congestion and increased travel demand. When a new transit system is introduced in a densely developed area, understanding the factors that influence ridership becomes crucial. Understanding the travel demand for systems such as metro or subway networks, especially during their pre-operational phase, is essential for assessing prospective users' perceptions and behavioral intentions (Liu et al., 2020). This is especially important given the complexity and ever-changing nature of travel behavior, which is affected by factors such as age, population, economic development, and the emergence of new modes of transportation (Feng et al. 2017; Chou et al. 2024). Dhaka, one of the fastest growing cities in Southeast Asia, has recently launched its first metro rail line, MRT line 6, marking a significant step toward transforming urban mobility in Bangladesh. Aiming to improve connectivity and ease congestion in heavily built-up areas, the MRT system aims to redefine transportation in the capital and its surrounding regions.

Urban planners and transportation engineers frequently attempt to generalize findings from developed countries to developing nations such as Bangladesh, but this approach can lead to significant issues, such as vulnerable transportation networks and fragmented urban development, which pose distinct challenges. The spatial and developmental characteristics of built-up areas in developing cities differ substantially from those of planned urban environments. In planned cities, the road network is established first, followed by the construction and development of the city. However, in existing built-up areas, existing land use pattern typically remains unchanged. As a result, when a new mode of transportation is introduced, the factors influencing ridership are expected to differ between stated and revealed preferences. Historically, Dhaka residents had to choose between private vehicles or affordable public transit options, primarily buses. The introduction of the MRT adds a new decision-making factor: it offers reduced travel times but relatively at a higher cost. Though fare is a key determinant influencing transportation choices, Dhaka's severe congestion introduces additional complexity, requiring people to weigh the trade-off between cost and time. Many work-life balance initiatives assume that individuals value spending more time with their families, a consideration that may interact with fare structures and influence how commuters prioritize between saving money and saving time.

This research explores the development of the MRT system in Bangladesh by examining the factors that influence ridership. People's perceptions of MRT regarding convenience, safety and reliability significantly impact their decision to use it. If individuals perceive MRT as reliable, safe, and accessible, they are more likely to choose it as their daily mode of transportation. This study investigates the role of attitudinal attributes in shaping the mode choice of MRT users. Understanding these factors are particularly important in densely built-up areas, where the success of one metro line can influence decisions about future expansions. In Bangladesh, for example, five additional MRT lines are currently in various stages of planning and construction. Research like this plays a vital role in helping cities identify what drives MRT usage, making it easier to design systems that are accessible, efficient, and responsive to public needs.

Recent studies have demonstrated that machine learning outperforms logit models in predictive accuracy (Habib & Nurul, 2012; Golshani et al., 2018; Cheng et al. 2019; Zhao et al. 2020). However, there is little research gap as these studies often prioritize prediction accuracy over interpreting ML models to understand behavior. In addition, there are limited studies regarding road users' attitude and perception of MRT in the context of built-up environment. This research integrates SHAP analysis and ML models to enhance predictability while providing valuable insights into the key variables influencing mode shifts. By considering individuals' sociodemographic profiles, attitudinal perceptions, and trip-related characteristics, the study highlights the most influential attitudinal factors in mode choice. It also underscores the potential of machine learning for both interpretability and predictability, particularly in Bangladesh, amid its evolving transport infrastructure.

2. LITERATURE REVIEW

Understanding passengers' behavioral intentions after experiencing transit services is an essential task for public transit managers, which can help in defining effective strategies to meet passengers' needs, retain existing passengers, and attract new ones (Lai et al., 2011). Dhaka, the capital of Bangladesh, faces a critical transportation crisis due to rapid population growth, uncontrolled urban sprawl, and predominance of private vehicles, rickshaws, and buses, resulting in severe congestion, pollution, and inefficient public transit. The introduction of MRT line-6 represents a high-capacity, sustainable alternative, promising faster and more reliable travel. However, challenges such as high fares, lack of integrated feeder services, and spatially uneven urban development threaten its success. To ensure long-term sustainability and accessibility, strategic land-use planning and transit-oriented development are essential to attract diverse ridership and maximize the system's benefits.

Dhaka's first MRT system aims to address the city's severe congestion caused by rapid population growth, unplanned urban development, and reliance on informal transport modes. However, its success depends on several factors, including fare affordability, integration with other transport modes, and spatial accessibility. Research highlights the rapid increase in private vehicle ownership due to unreliable public transport (Lai et al., 2011), making the MRT a potential alternative. Yet, spatial heterogeneity in Dhaka complicates accessibility, with uneven distribution of residential and commercial areas limiting ridership potential (Chowdhury et al., 2012). Effective integration of informal modes like rickshaws and minibuses is essential for last-mile connectivity (Liu et al., 2020), but their unregulated operations pose challenges. Affordability is another concern, as low-income commuters reliant on inexpensive transport options may find MRT fares prohibitive (Ortuzar & Willusen, 2001). Additionally, the MRT's introduction could reshape land use through the "transit premium," as seen in global contexts (Paulssen et al., 2014), emphasizing the need for equitable policies to ensure benefits for all residents. To succeed, Dhaka's MRT must address these local challenges while learning from global best practices, creating a context-appropriate, accessible and efficient transportation system.

Modal shift studies aim to assess passenger willingness to shift from one mode to another mode of travel, chiefly in urban regions. Transport modal choice can be influenced by personal characteristics, trip characteristics, and attributes of the environment such as land use, accessibility, and availability of transit services (Ortuzar & Willusen, 2001). Other factors include the local psychosocial values, mobility biographies due to life-course transitions, and national economic policies (Chowdhury et al., 2012; Salas et al., 2022). Previous studies in different cities have shown that transport modal shift could be influenced by: the original transport mode, trip frequency, geographical location, trip distance, trip duration, cost, and purpose of trips (Van der Warden et al., 2008); public transport use was induced by parking problems, and vehicle accessibility especially among students in Australia (Corpuz, 2007), whereas in Malaysia, studies by Nurdden revealed that the preference towards public transport could be encouraged by fare subsidy, reduced transit time, reduced distance from home to transit stations, and home to work location (Nurdden et al., 2007). Apart from these factors, attitudinal perceptions of users also influence user's mode choice. Lai and Chen examine the connections between passenger behavioral intentions and the many elements that influence them (Lai & Chen, 2011). Aside from the elements highlighted by previous research, such as service quality, perceived value, and satisfaction, this study focuses on the role of public transportation services in passenger behavioral intentions. Eboli and Mazzulla developed a SEM to investigate the association between worldwide consumer satisfaction and service quality criteria, including safety, cleanliness, primary and supplementary services, information, and staff (Eboli & Mazzulla, 2012). Thus, intention toward transit services is an important concept that underpins modeling future use of public transit and strategies to enhance market share. A person's intention to perform behaviors is a strong predictor of actual behaviour (Aizen & Driver, 1991). For instance, Hensher analyzed commuters' intentions to shift to a forthcoming metro service from currently available modes (Hensher, 2017). Yang et al. studied commuters' mode choices before and after the introduction of a public bicycle system (Yang et al., 2016). Resdiansyah observed the choice preferences between old bus vehicles currently in use and new bus vehicles to be available shortly (Resdiansyah, 2021)

In the commuting behaviour literature, collected data are widely used to calibrate discrete choice models, i.e., by capturing commuters' actual choice observations. Early work focused on the relationships between commuters' mode choices and residential choices (DeSalvo & Huq, 2005). Recent studies have proposed in-depth explanations for departure time choices and mode choices using various discrete choice models. For example, Habib used a discrete–continuous combined framework to model the travel modes, work start times, and durations of joint choice behaviors (Habib & Nurul, 2012). Sasic and Habib used a generalized extreme value model to investigate commuters' departure time choices. Ding et al. Studied the joint choice of travel mode and departure time using a crossed-nested logit (CNL) model. Calastri et al. applied evolutionary game theory to the binary choice between public transport and private cars (Calastri et al., 2019).

However, in recent years, machine learning methods based on big data have been widely applied in transportation fields, and they show high predictive performance that surpasses classic discrete choice models (Rao, 2019; Zhao et al., 2020). In recent years, machine learning methods have attracted much attention for analyzing travel mode choice. Pineda-Jaramillo and Arbelaez-Arenas compared different logit models and machine learning models and found that the optimized gradient boosting model outperformed the compared models. Mi et al. proposed a softmax regression machine learning algorithm to predict travel mode and the results showed that the prediction accuracy was higher than with the SVM and multinomial logit (MNL) models. Salas et al. provided a systematic comparative evaluation of machine learning and discrete choice models and found that neural networks outperform other models, including the MNL, mixed multinomial logit (MMNL), k-nearest neighbor (KNN), SVM, random forest (RF) (Salas et al., 2022).

3. METHODOLOGY

3.1 Data collection and data preparation

3.1.1 Data collection

Four MRT stations were selected for the home interview survey (HIS) considering a 1500 m buffer area namely: Pallabi, Kazipara, Bijoy Sharani, and Motijheel represent 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.

3.1.2 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.

3.1.3 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 1,533 participants, meeting the criteria set for quality and completeness. A total of 1,726 responses were collected, and after data cleaning, 1,513 responses remained removing the outliers.

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.

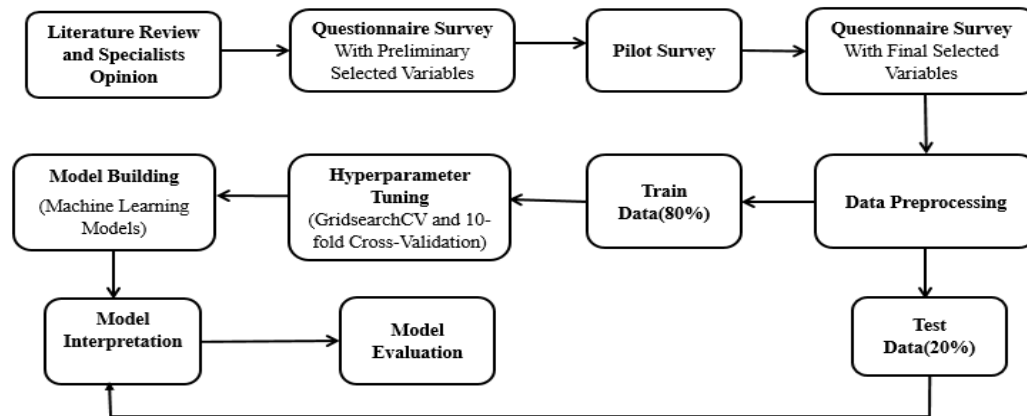


Figure 1: Methodological Workflow

A diagram of methodological workflow is shown in **Figure 1**. Firstly, survey locations are selected and buffer areas are selected from literature review. Then the number of samples to be selected from each buffer zone using DAP is determined. Initially, preliminary variables for the questionnaire survey are selected based on an extensive literature review. 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 nine operational metro stations. After the data pre-processing part two ensemble model, ANOVA and random forest (RF) are used to select the most influential variables. This was followed by grid search cross-validation for hyperparameter tuning to enhance model performance. Machine learning models, i.e., RF, SVM are used for data analysis, with the models run using the selected variables. The best model, based on accuracy, is then identified and thoroughly interpreted. Simultaneously, the model is evaluated to determine if the selected variables adequately explain it based on feature importance which reflects the contribution of each variable to the model's predictive accuracy. Essentially, it assesses how vital a specific variable is for the model and its predictions.

3.1.4 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, including age, gender, sex, household income, employment status, and educational attainment, fall under the first category of socio-demographic variables while the second area devotes itself to elements particular to the method of transportation and includes parameters like waiting time, in-vehicle travel time, fare, and distance to the final destination. 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.

3.2 Data Pre-processing

The study sampled 2,175 participants, split into a pre-test and main study group, to refine and validate survey methodologies.

Out of 196 participants, most provided feedback under supervision but 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. Refined methods engaged 1,979 participants, significantly reducing the dropout rate. Of these, 1,701 completed the survey, and 1,533 responses met the required quality standards. Active monitoring and follow-ups

ensured data reliability and integrity. This phased approach ensured a robust survey design and high-quality data collection.

3.3 Random Forest (RF)

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique which can be used for both classification and regression problems in ml. Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. While decision trees consider all the possible feature splits, random forests only select a subset of those features (Liaw et al., 2002).

3.4 Support Vector Machine (SVM)

Support vectors are simply the coordinates of individual observation, and a hyper-plane is a form of svm visualization. The SVM classifier is a frontier that best segregates the two classes (hyper-plane/line). The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane (Smola et al., 2004).

3.5 SHapley Additive exPlanations (SHAP)

SHAP is well known for enhancing the interpretability of machine learning models and has been increasingly valued for its effectiveness in pinpointing important features across various contexts. Traditional feature importance techniques typically offer only a global ranking of variables and fail to show their influence on specific predictions. SHAP overcomes this limitation by measuring the contribution of each feature to individual instances (Parisineni et al., 2024).

4. RESULTS AND DISCUSSIONS

4.1 Model Formulation

4.1.1 Most Influential Variable Selection

A two-step approach has been used for selection of influential variable using analysis of variance (ANOVA) and random forest (RF).

The dataset for this study consisted of input features related to forecasting of MRT ridership aspects. Selection of variables from using k-best selection method based on variance score (ANOVA) and random forest feature importance score based on Gini Index which means how much each feature contributes to the statistical dispersion of all variables. After combining from ANOVA and random forest the best variables are:

Table 1: Selected Attitudinal Variables for MRT Ridership

Rank	Influential Attitudinal Variables	Encoded Variable Names in Models
1	Work-Centric Attitude during Commute	Work_cen
2	Perception of Pedestrian Infrastructure to the Transit Stop	Ped_Infra
3	Safety of the Preferred Mode	Safety
4	Inclination to Family	Family_incl
5	Reliability of the Preferred Mode	Realibility
6	Inflation of the Preferred Mode	Inflation_conc
7	Flexibility of the Preferred Mode	Flexibility
8	Activities Performed by Users during Commute	Activity_During_Trvel
9	Walking as a Benefit	Walking_ben
10	Social Influence in Transport	Social_influence

Table 1 highlights the most influential variables chosen for model formulation. Initially, all variables were considered, and influential ones were identified based on the analysis of variance (ANOVA) score. Subsequently, these variables were ranked using the random forest feature importance score. The two scores were then combined through a weighted average, and the top 10 variables were selected as input variables for the model. The output variable indicates whether the respondent is likely to use MRT.

4.2 Model Evaluation

The prior task before building the models was to determine the optimized parameters by tuning each of the 2 models (RF, SVM) with different combinations of hyperparameters on the training data. A gridsearch cross-validation with 10-fold cross-validation technique was used for tuning.

From the model, RF model's best hyperparameters are found: number of estimators: 100, criterion: gini, maximum tree depth: none, minimum number of samples at leaf node: 1, minimum number of sample split: 2. Best hyperparameters for SVM are, regularization parameter:100, kernel: radial basis function, kernel coefficient: auto.

Accuracy of the machine learning model, RF and SVM are given below.

Table 2: Model Accuracy

Model Parameters	SVM	RF
Accuracy	70.63%	73.07%

The RF model achieved an accuracy of 73.07%, while the SVM model reached 70.63%, indicating that RF is the more accurate model. Confusion matrix of both the models are given below.

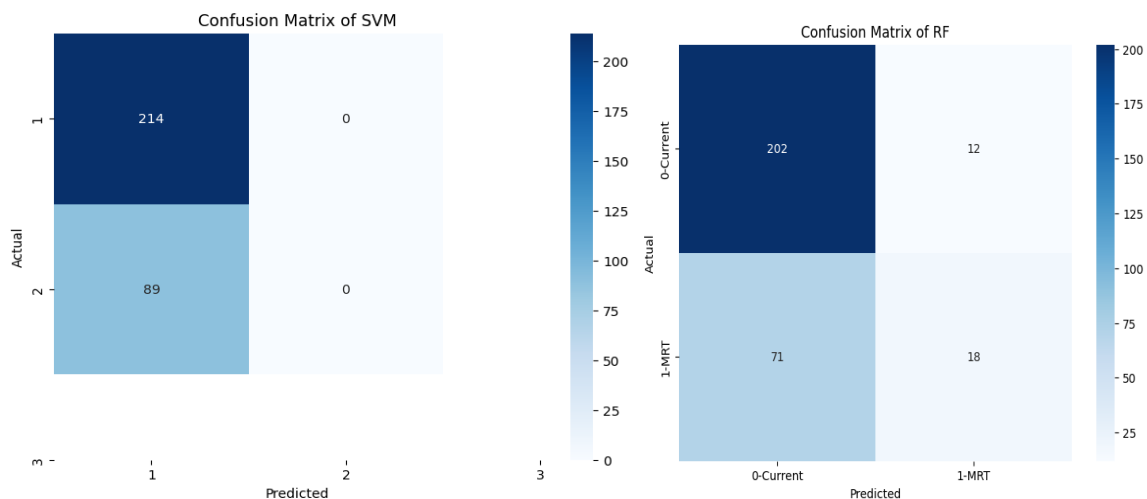


Figure 2: Confusion Matrix of SVM and RF model

In **Figure 2**, the confusion matrix is presented, derived from the best-performing model, random forest. The RF model demonstrates exceptional performance in accurately predicting MRT users, with only a minimal number of false negatives (misclassifying MRT users as non-MRT users).

4.3 Model Interpretation

In this paper, the model-based feature importance technique was used to identify the influential features and their contributions to model prediction. As RF was chosen as the best model, the correlation of the variables with MRT ridership were done using SHAP value. The importance of these variables was ranked based on the mean SHAP value and a summary plot of the SHAP values are shown below:

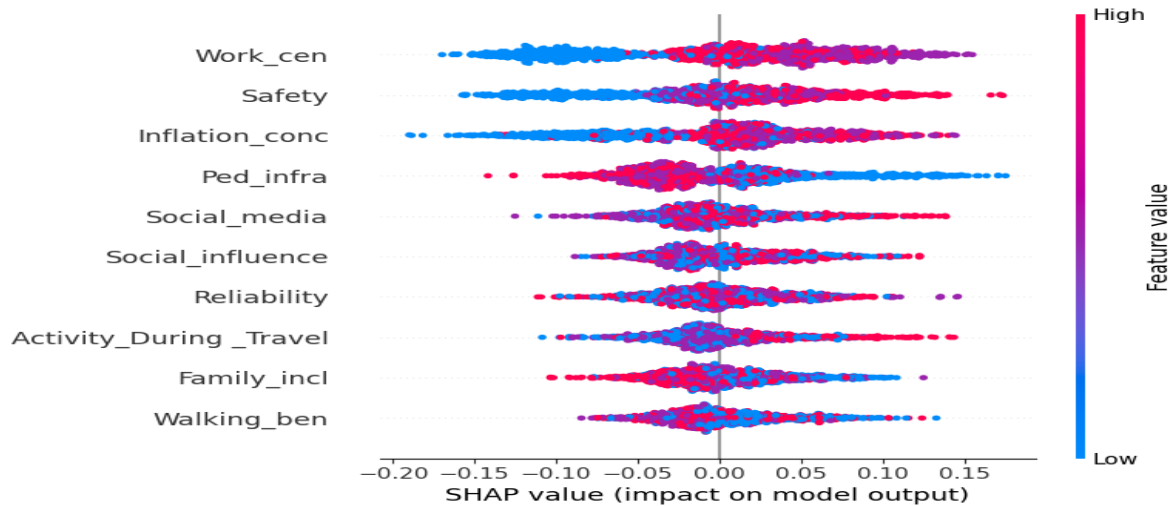


Figure 3: Random Forest Feature Importance of RF Model

Figure 3 presents SHAP summary plots illustrating the relative importance and direction of influence of attitudinal factors on metro ridership prediction. The x-axis represents SHAP values, which measure the magnitude and direction of each feature's contribution to the model output. Positive SHAP values indicate features that increase the likelihood of MRT usage, while negative values reflect features that reduce it. The color gradient from blue representing low feature value to red indicating high feature value demonstrates how variations in each attribute influence the model's prediction.

In the model, the SHAP values range approximately from -0.2 to $+0.15$, capturing the marginal effect of each attitudinal factor on MRT mode choice. Among these, work-centric attitude during commute (*Work_cen*) exhibits the highest impact, suggesting that individuals whose workplaces are located in or near station areas are more likely to prefer MRT due to its convenience, time savings and accessibility. For respondents whose workplaces are distant from MRT station, MRT is less attractive because access and egress cost and distance reduces benefits of MRT. Safety and inflation concern of the preferred mode also show significant influence. The positive SHAP values associated with higher safety perceptions indicate that commuters valuing secure and reliable travel tend to favor MRT. Higher inflation concerns have a positive impact represented by red points on the right side of SHAP value, implying that individuals sensitive to increased living and transportation cost changes, are more likely to adopt MRT. It represents that if transportation sector has higher inflation rate, possibly causing rising fuel prices or car maintenance costs, people will shift their mode of transportation to MRT, increasing MRT ridership. In that case, MRT will be considered a more affordable and stable cost option compared to other modes of transport, such as taxis, cars, or private vehicles, which may experience price hikes.

An interesting observation is that when pedestrian infrastructure is well-developed, it tends to decrease the likelihood of choosing MRT for daily transportation. This is because high-quality pedestrian infrastructure provides better access to walkable routes and safer sidewalks, encouraging people to opt for active modes of transport like walking or cycling, especially for short-distance

travel. With increased walkability, individuals can easily reach their destinations on foot, reducing the need for MRT. Consequently, the demand for MRT may decline for shorter trips where walking is a more convenient option.

Additionally, social media, social influence, and reliability show a mix of red and blue spots, indicating that their impact is not consistent and varies based on the specific value of each feature. The effect of these factors on choosing MRT depends on different conditions and individual perspectives, making them more context-dependent. For example, if MRT is perceived as more reliable than other transportation options, people are more likely to choose it for daily commuting. However, individuals who have traditionally relied on other modes like buses or private cars may be less inclined to switch to MRT. Social factors, such as social media and social influence, also play a significant role; individuals exposed to positive opinions or discussions about MRT on social networks are more likely to use it. Conversely, factors like activity during travel and family inclination have moderate but mixed effects, suggesting that the ability to engage in productive activities while traveling or family-related travel preferences may influence MRT use differently among groups. Perceived walking benefits exhibits a relatively smaller effect, indicating that although physical activity benefits are acknowledged, they are not major determinants of MRT choice.

In summary, the SHAP distribution reveals that attitudinal and perceptual attributes particularly workplace location, safety perception, and pedestrian infrastructure play crucial roles in shaping MRT ridership. Understanding users' attitudes and perceptions toward MRT can assist policymakers in improving the system's overall performance and attracting a larger user base by optimizing MRT services.

5. CONCLUSIONS & POLICY IMPLICATIONS

Rail-based transit systems in developing countries like Bangladesh play a vital role in addressing urban traffic congestion and meeting the growing demand for transportation. Encouraging commuters to shift from private vehicles to public transit requires addressing various factors that influence mode choice. In this study, revealed preference surveys were conducted at MRT stations to identify the most influential variables affecting MRT usage.

This research develops RF and SVM model to assess attitudinal variables influencing MRT ridership in the context of developing country like Bangladesh. RF analysis achieved the highest accuracy in predicting attitudinal factors of mode choice. RF model consistently highlights work centric attitude during commute emerges as the most influential factor for choosing MRT. One interesting factor found is pedestrian infrastructure which implies that better walking facilities increases active mode travel thus reducing short distanced travel by MRT. Other critical factors influencing MRT adoption include safety, reliability, social influence and flexibility of the preferred mode etc.

Thus, to boost MRT adoption, policymakers should prioritize safety and convenience, enhance service quality, and emphasize the advantages of MRT, such as flexibility, reliability, time savings, and improved accessibility. Implementing integrated feeder service and pedestrian infrastructure could make MRT more appealing for medium and short distanced travel. Additionally, addressing safety concerns, particularly for women and during late hours, is equally essential. Increasing the presence of security personnel and surveillance systems at MRT stations and in transit areas would enhance safety. Also, to meet the demand of female commuters, the number of dedicated coaches for women should be increased.

By gaining a better understanding of commuter behavior and preferences, transit authorities can adopt strategies that not only retain current users but also attract new ones. These efforts will support the successful adoption and long-term viability of MRT systems in rapidly growing urban areas. As Dhaka expands its metro network with five new lines, the study emphasizes the need for policies that enhance physical access and affordability while also addressing user perceptions and behaviors. These insights can help shape targeted interventions, such as safety improvements, public awareness

campaigns, and technology integration, ultimately promoting greater acceptance of MRT as a sustainable urban transportation solution.

DECLARATION OF USE OF AI

The authors declare that no artificial intelligence (AI) tools or technologies were used in the preparation, writing, editing, analysis, or interpretation of this manuscript. All aspects of the research and manuscript preparation were conducted solely by the authors.

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