

SERVICE QUALITY PERCEPTIONS AT MAJOR BUS TERMINALS OF DHAKA, BANGLADESH USING RANDOM PARAMETER ORDERED PROBIT MODEL

Mahibul Taohid Aditya^{1*}, Md Bayezid², Sharbuni Akter³, and Shajute Sharker⁴

^{1*}Lecturer, Department of Civil Engineering, Dhaka International University, Dhaka, Bangladesh. e-mail: taohid.aditya@gmail.com

² Student, Department of Civil Engineering, Islamic University of Technology, Gazipur, Bangladesh, e-mail: bayezid@iut-dhaka.edu

³Student, Department of Civil Engineering, Dhaka International University, Dhaka, Bangladesh, e-mail: sharbuniakter3759@gmail.com

⁴Student, Department of Civil Engineering, Dhaka International University, Dhaka, Bangladesh, e-mail: shajutesarker807@gmail.com

***Corresponding Author**

ABSTRACT

The rapid urbanization and the increasing reliance on buses as the most significant form of transport in Dhaka have put significant pressure on the infrastructure of the stations, their effectiveness, and the quality of service as a whole, contributing to the consistent commuter dissatisfaction. This research determines and measures the causes of passenger satisfaction in large urban bus stations through a Random Parameter Ordered Probit Model (RPOPM) with Average Marginal Effects (AMEs) that allows a related evaluation of the heterogeneity of preferences as well as the influence of a probabilistic attribute. The model yields significant explanatory power (pseudo- $R^2 = 0.4041$) using primary data as observed among 527 passengers in the Gabtoli and Mohakhali terminals and Abdullahpur terminals. Some of the service attributes have statistically significant random parameters, which means that there is a significant difference in user perceptions. The safety facilities of women, the overall station security, the cleanliness of toilets, the visibility of staff and their responsiveness, and the condition of vehicles are always positively related to the chances of higher satisfaction. and ineffective ticketing system, an insufficient digital platform, and overcrowding considerably reduce the chances of positive ratings. The further results of AME show that the most significant changes in upward probabilities are caused by the enhancement of safety and hygiene attributes, which increases the likelihood of users experiencing good or excellent satisfaction significantly as compared to the baseline conditions. Increases in the staffing and communication services also bring moderate but significant benefits, whereas the improvement in the condition of the vehicles creates stable positive effects on the groups of passengers. On the whole, the combined RPOPM and AME analysis helps to highlight the fact that low-cost interventions, especially those targeting safety assurance, cleanliness, and information management, can cause disproportionately high shifts in perceived service quality, and, therefore, allow large, high-demand bus terminal management in developing megacities like Dhaka to pursue more user-centric and resource-conscious approaches to the work.

Keywords: *Passenger Satisfaction; Bus Station; Service Quality; Random Parameter Ordered Probit Model; Econometric Modelling; Average Marginal Effect*

1. INTRODUCTION

The major mode of transport in developing megacities is still the public transport, which has supported the mobility of the urban population, but the rapid process of urbanisation has surpassed the capacity of the infrastructure, and this has led to overcrowding, delays in service provision, and low customer satisfaction. Stations form the most important interface between passengers and the transport system in bus-dominant systems, as they create sensations of reliability, comfort, and safety (Redman et al., 2013; Eboli and Mazzulla, 2007). Although such large-scale projects as Bus Rapid Transit (BRT) and Mass Rapid Transit (MRT) can be seen as long-term capacity expansion, the long gestation period of these projects implies that millions of people in their daily lives use their under-maintained and unmanaged stations, which directly affects the perceived quality of the service. Accordingly, station-level conditions improvement can be viewed as a low-cost and short-term instrument of improving user experience and motivating people to keep using public transport (De Oña, & De Oña, 2015; Mouwen, 2015).

Service quality theory assumes that the satisfaction of passengers is determined by the technical quality- the service provided, and the functional quality- how the service is provided, mediated by expectations and system image (Khatun et al, 2025). The dimensions, at the station level, correspond to the visible features of the stations, like cleanliness, lighting, ventilation, availability of seats, staff behaviour, access to information, safety provisions, and so on. Even small changes in these tangible qualities in resource-restrained urban settings such as Dhaka can contribute to a disproportionate increase in perceived satisfaction. However, the majority of empirical research studies in developing nations are based on descriptive rankings or simple regressions that ignore the heterogeneous sensitivities of users and the probabilistic response of satisfaction.

The example of Dhaka, the capital of Bangladesh, can be used to illustrate the problem of a bus-reliant megacity that faces severe congestion, poor service delivery, and limited passenger facilities. The users frequently encounter congested areas, poor shading and ventilation, unclean waiting rooms, low security levels, and poor ticketing (Ali, 2010; DMTCL, 2016). Though infrastructure investments are ongoing, the immediate user experience remains tied to the quality of these station-level services. Determining what factors are the strongest determinants of satisfaction and how their impacts differ among groups of passengers is essential in prioritising where budgets are constrained. Current methods like SERVQUAL or basic Ordered Probit Models provide mean-level insights but ignore the unobserved heterogeneity, i.e., the variation in the perception and importance that passengers attribute to each attribute.

An emerging literature has modelled the satisfaction of public transport users, but most studies generally assume that users are homogeneous in their preferences and thus do not consider the diversity brought about by demographics, purpose of using the transport, and past experiences (Beirão and Cabral, 2007; Hensher and Greene, 2003). The given assumption restricts the policy relevance because interventions that may be effective with one segment of the users may not be equally applicable to others. Random Parameter Ordered Probit Model (RPOPM) addresses this issue by allowing selected coefficients to vary randomly across individuals, which captures both the mean effects and preference dispersion (Khatun et al., 2025; Train, 2009; Greene and Hensher, 2010). Besides, the use of Average Marginal Effects (AMEs) converts statistical findings into readable probability change across levels of satisfaction, which is informative to policy makers in knowing the potential level of improvement in each station attribute. Their application to a developing nation scenario like Dhaka, therefore, helps both in terms of methodology and practice: it enhances the knowledge of heterogeneous perceptions and aids data-driven prioritisation of station-level interventions.

The general aim of the research is to quantify and interpret the effect of station-level characteristics on passenger satisfaction in a bus-dominant developing city, considering heterogeneity in user preferences. In particular, the research seeks to identify and rank the strongest station features that influence passenger overall satisfaction in bus terminals in urban areas, to estimate a Random Parameter Ordered Probit Model (RPOPM) that can be used to capture the magnitude and variability of the attribute effects on passenger groups, to calculate and interpret Average Marginal Effects (AMEs) for each significant attribute, providing indications of how improvements in specific service

dimensions can alter the probability of higher satisfaction, and deriving low-cost, high-impact interventions that can enhance passenger experience. Ultimately, the study bridges the gap between behavioural econometric modelling and operational decision-making in the context of public transport service quality.

2. LITERATURE REVIEW

2.1. Service Quality and Passenger Satisfaction

Service Quality in public transport is inherently a multidimensional category, including both tangible and intangible elements of the travelling experience (Sogbe et al., 2025). Classical models make a distinction between the technical quality, referring to the outcome of the service, and the functional quality, which refers to the process of the delivery (Hussain et al., 2025). These, in the station environment, would be cleanliness, comfort, safety, accessibility, and information clarity (Eboli & Mazzulla, 2007; Dell’Olio et al., 2011). Several studies have also established that the perceived service quality is a strong determinant of satisfaction, which subsequently leads to loyalty and subsequent ridership (Bolton and Drew, 1991; Mouwen, 2015). Among the numerous determinants, reliability, comfort, cleanliness, and safety are the most evident features that influence the judgments of users on the system of public transport (Redman et al., 2013).

2.2. Station-Level Attributes and Perceived Experience

Stations and terminals are the first and last touchpoints within the travel experience of a passenger, where perceptions are formed and reinforced (De Oña & De Oña, 2015). The waiting environment, the intensity of crowding, ambient climatic conditions, and the availability of security personnel, among others, have a significant impact on the perceived travel burden. The perceived waiting time and consequent anxiety are mitigated through the improvement in lighting, ventilation, and seating availability (Eboli & Mazzulla, 2007). Similarly, the visibility and helpfulness of the staff, as well as the clarity of the signage and information kiosks, increase the perceived reliability and safety. The factors are particularly critical in emerging urban settings where limited resources make small-scale, high-impact interventions more feasible compared to large-scale infrastructure renovations.

2.3. Passenger Heterogeneity and Advanced Modeling Approaches

Recent research has shown that not all passengers appreciate service attributes equally. Differences in age, gender, purpose of travel, and frequency of use create substantial heterogeneity in satisfaction responses (Beirão & Cabral, 2007; Nordfjærn et al., 2014). Traditional models, including basic Ordered Probit or SERVQUAL models, assume homogenous preferences and thus can’t detect these variances. On the contrary, Random Parameter models (also known as Mixed models) allow the parameter estimates to vary across individuals to reveal the reaction of different user groups to the conditions of the station (Train, 2009; Greene and Hensher, 2010). The Random Parameter Ordered Probit Model (RPOPM) extends this logic to ordinal outcomes such as satisfaction ratings, enabling estimation of both average effects and the distribution of sensitivities around those means (Hensher, Rose, and Greene, 2015).

The concurrent calculation of Average Marginal Effects (AMEs) is an extension of the RPOPM since the latent coefficients are turned into probability shifts in each category of satisfaction. This translation from latent coefficients to probability shifts makes econometric results actionable for decision-makers (Greene & Hensher, 2010; De Oña & De Oña, 2015).

2.4 Application in Developing-Country Contexts

In developing contexts like Dhaka, the methodological gap remains substantial. Previous research has mainly relied on gap-score or regression methodology to determine service deficiencies (Ali, 2010; Aidoo et al., 2013). These methods, although descriptive, lack behavioral interpretation and do not capture heterogeneity. Advanced econometric models, like the RPOPM, are rarely used despite their ability to not only determine what attributes are important, but also the scale and heterogeneity of their impacts. With the inclusion of AME analysis, policymakers can measure the improvement priorities in a probabilistic manner, thus optimizing the limited resources against the largest number of passengers affected.

Summing up the above, the passenger satisfaction with the bus station services can be achieved due to various attributes, which are interrelated, such as comfort, safety, accessibility, and information delivery. The evidence in the literature is consistent that interventions at the station level can have a significant effect on perceived quality, especially in resource-limited urban environments. However, traditional models overlook the heterogeneity in preferences, thus giving a partial picture and poor policy targeting. This paper empirically paves the way by using the Random Parameter Ordered Probit Model (RPOP) and the Average Marginal Effects (AME) to identify both the mean and individual-level sensitivity of satisfaction response. It provides a framework for improving passenger experience in urban centers by focusing on bus terminals in Dhaka, cost-effectively.

3. STUDY AREA AND DATA COLLECTION

3.1. Study Area

The study was carried out in 3 large intercity bus terminals in Dhaka- Gabtoli, Mohakhali, and Abdullahpur. The analysis is specifically focused on large intercity terminals and is not aimed at reflecting smaller neighborhood terminals, informal boarding spots, and stations found in other cities in Bangladesh. These terminals serve most of the long-distance passengers of Dhaka and differ in land use surrounding, route coverage, and management practices. This heterogeneity gives us a representative view of the experiences of passengers in a wide variety of service settings. The survey was conducted at terminal concourses as well as near the boarding bays in order to capture the instant perceptions after the actual travel experiences. The presence of various terminals allowed comparing different conditions of operation and environment, so that the results are representative of a wide cross-section of the passenger opinion in the bus system of Dhaka.

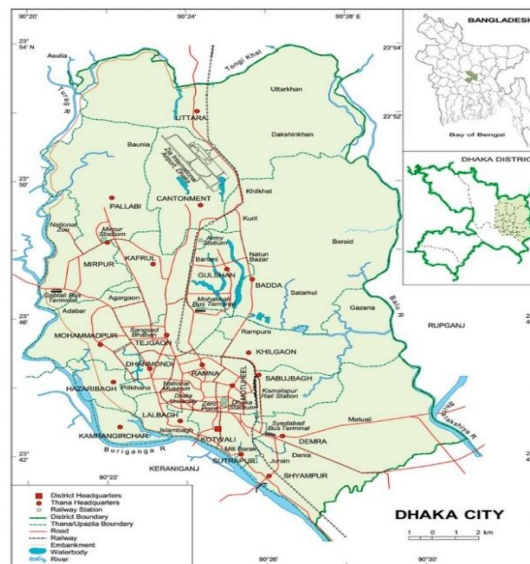


Figure 1: Map of Dhaka

3.2. Questionnaire Design and Pilot Testing

A Random Parameter Ordered Probit Model is employed to capture unobserved heterogeneity in passenger perceptions, allowing selected service attributes to vary across individuals. This approach relaxes the restrictive assumption of homogeneous preferences and provides a more behaviorally realistic representation of satisfaction responses in high-demand urban bus terminals. Primary Data was collected through an in-person questionnaire survey administered at the three terminals. The structured item consisted of four parts: passenger demographics (age, gender, education, occupation, income), attributes of trip (purpose, frequency, class of travel), ratings of station-level attributes (cleanliness, toilet facility, lighting and ventilation, visibility of staff, safety, women facilities, information booths, ticketing, and space inside the bus), and the level of overall satisfaction.

Responses were recorded digitally by trained enumerators during regular operating hours to minimize input errors. A pilot test was done to maintain the clarity, consistency, and proper timing. Upon the screening of responses that were missing, inconsistent, or duplicate, 527 viable observations were conserved to be analyzed. Categorical variables were encoded into ordered or dummy formats depending on their role in the model, and multicollinearity tests were performed to ensure stable coefficient estimation.

This dataset provides a statistically sufficient sample in terms of modeling ordinal satisfaction outcomes, while maintaining the variability necessary for identifying heterogeneous passenger responses.

4. MODELING METHOD

4.1. Variable Selection and Construction

Before estimating the Random Parameter Ordered Probit Model, a fixed-parameter Ordered Probit Model was used for variable screening and multicollinearity control. Variables exhibiting unstable coefficients or redundancy across alternative specifications were excluded to ensure a parsimonious and statistically robust final model. Explanatory variables were selected based on established public transport service quality literature and station-level satisfaction frameworks, followed by pilot testing and multicollinearity screening. The final variable set reflects key safety, hygiene, comfort, and information-related attributes relevant to large urban bus terminals. The dependent variable, satisfaction of passengers, was measured on an ordinal scale. From the survey, after data cleaning and removing multicollinearity, 12 independent variables were developed, covering attitudinal, perceptual, and environmental variables, and also socio-demographic perspectives.

4.2. Model Specification

The ordered probit model operates on the principle that an observed ordinal variable (y) corresponds to an underlying unobserved continuous variable (y^*) that ranges from negative to positive infinity. In this study, y denotes the satisfaction level, categorized into four ordered responses: 'Not Satisfactory,' 'Below Average,' 'Average/Good,' and 'Excellent.' The measurement framework expresses the latent variable y^* , representing the underlying tendency toward horn usage frequency, as follows:

$$y_i = j \text{ if } \tau_{j-1} \leq y_i^* < \tau_j \text{ for } j = 1 \text{ to } 4 \text{ in our study} \quad (4.2.1)$$

here the τ values serve as thresholds or cut points dividing the intervals. The extreme categories (1 and 4) have open-ended intervals with $\tau_0 = -\infty$ and $\tau_4 = \infty$. Accordingly, the observed level of horn usage (y) is determined using these thresholds as:

$$y = \begin{cases} 1 & \text{if } -\infty \leq y_i^* < \tau_1 \text{ (Not Satisfactory)} \\ 2 & \text{if } \tau_1 \leq y_i^* < \tau_2 \text{ (Below Average)} \\ 3 & \text{if } \tau_2 \leq y_i^* < \tau_3 \text{ (Average / Good)} \\ 4 & \text{if } \tau_3 \leq y_i^* < \infty \text{ (Excellent)} \end{cases} \quad (4.2.2)$$

The structural form of the ordered probit model, representing individual observations (in this context, each driver), is defined as:

$$y_i^* = \beta_0 + x_i\beta + \varepsilon_i \quad (4.2.3)$$

The estimation of β using the Maximum Likelihood (ML) approach requires an assumption about the distribution of the error terms (ε). ε is assumed to follow a normal distribution with a mean of 0 and a variance of 1. Consequently, the Cumulative Distribution Function (CDF) and Probability Density Function (PDF) are given as:

$$\varphi(\varepsilon) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\varepsilon^2}{2}\right) \quad (4.2.4)$$

$$\Phi(\varepsilon) = \int_{-\infty}^{\varepsilon} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt \quad (4.2.5)$$

Once the error term distribution is defined, the probability of observing a specific category of y given x can be calculated. The predicted probability for a particular horn usage category ($y = j$) is expressed as:

$$Pr(y_i = j | x_i) = \Phi\{\tau_j - (\beta_0 + x_i\beta)\} + \Phi\{\tau_{j-1} - (\beta_0 + x_i\beta)\} \quad (4.2.6)$$

The model is inherently unidentifiable since shifts in the threshold parameters (τ_1 , τ_2 and τ_3) can offset changes in the intercept term β_0 . To resolve this issue, one common identification approach involves fixing either the intercept (β_0) or one threshold to zero. The estimated probabilities and statistical significance tests derived from Equation (4.2.6) remain unaffected by this assumption. For simplicity, β is set to 0 in this study.

The final log-likelihood is expressed as:

$$\ln(L) = \sum_{i=1}^n \sum_{j=1}^4 d_{ij} \ln[\Phi(\tau_j - x_i\beta) - \Phi(\tau_{j-1} - x_i\beta)] \quad (4.2.7)$$

Following Naik et al. (2016), the estimation process involves maximizing Equation (4.2.7) and solving for and using numerical optimization techniques such as the Newton-Raphson method. However, the conventional ordered model assumes homogeneous effects, limiting its ability to capture individual-level variation. To address this limitation, the Random Parameter Ordered Probit (RPOP) model allows parameter heterogeneity by incorporating an additional random term (γ_i) that captures unobserved individual-specific effects (Xie et al., 2020; Naik et al., 2016; Christoforou et al., 2010):

$$\beta_i = \beta + \gamma_i \quad (4.2.8)$$

The β_i of the systematic risk propensity function is thus distributed across individuals following specific distributions. Random parameter models are typically estimated using Halton draw-based simulated maximum likelihood techniques. In this study, a normal distribution was adopted, as it tends to provide a superior statistical fit (D'Agostino, 2017). The Random Parameter Ordered Probit Model was estimated using R and Python programming languages.

4.3. Computation of Average Marginal Effects

To enhance policy interpretation, Average Marginal Effects (AMEs) were derived from the RPOP results. AMEs measure how a one-unit change in an explanatory variable alters the probability of a passenger being in each satisfaction category. These effects translate the model's statistical outputs into practical, probability-based insights that indicate which service improvements yield the most substantial changes in satisfaction. For instance, improvements in women's safety facilities, toilet cleanliness, and visible security presence showed the largest positive AMEs, meaning that investment in these areas would most effectively raise passengers from "below average" to "good" or "excellent" satisfaction levels.

5. RESULT

Table 1: Random Parameter Ordered Probit Model Computation

Variables	Mean		Standard Deviation		Variables	Mean		Standard Deviation	
	Coefficient	P - value	Coefficient	P - value		Coefficient	P - value	Coefficient	P - value
Constant	1.052	0.047			Constant	1.052	0.047		
Age					Station Security				
18 – 35 Years	0.085	0.047*	0.002	0.123	Not Satisfactory	0.073	0.028*	0.157	0.024*
35 – 60 Years	0.113	0.039*	0.068	0.024*	Below Average	0.177	0.024*	0.072	0.025*
Travelling Class					Visibility of Station Staff				
Local Bus	-0.118	0.030*	0.008	0.05	Average	0.171	0.024*	0.031	0.024*
AC Bus	-0.138	0.028*	0.002	0.376	Good	0.213	0.024*	0.03	0.028*

Non-AC	-0.134	0.029*	0.033	0.025*	Not Satisfactory	-0.183	0.026*	0.109	0.025*
Sleeper Bus	-0.123	0.030*	0.06	0.023*	Below Average	-0.138	0.026*	0.015	0.033*
Business Class Bus	-0.204	0.027*	0.051	0.026*	Average	-0.103	0.028*	0.014	0.027*
Women's Safety Facilities					Good	-0.054	0.044*	0.001	0.851
Not Satisfactory	-0.438	0.024*	0.004	0.016	Ticket Buying Method				
Below Average	-0.359	0.024*	0.001	0.048	From the ticket counter	-0.066	0.031*	0.011	0.035*
Average	-0.283	0.025*	0.005	0.066	Mobile app / online	-0.089	0.028*	0.035	0.027*
Good	-0.232	0.024*	0.055	0.025*	From the bus conductor or after boarding	-0.086	0.027*	0.009	0.054
Excellent	0.08	0.025*	0.069	0.025*	Bus condition (AC-Fan-Light)				
Bus stop (Fixed or Random)					Not Satisfactory	-0.346	0.028*	0.062	0.025*
Mostly at designated stops	0.088	0.025*	0.016	0.025*	Below Average	-0.305	0.028*	0.032	0.027*
Sometimes anywhere	0.088	0.024*	0.029	0.023*	Average	-0.342	0.028*	0.05	0.026*
Often anywhere	0.074	0.024*	0.016	0.034*	Good	-0.348	0.027*	0.037	0.026*
Toilet Facility					Passenger Information Booth				
Not Satisfactory	-0.07	0.025*	0.081	0.024*	Very Crowded	-0.057	0.039*	0.007	0.094
Below Average	-0.08	0.024*	0.125	0.024*	Crowded	-0.079	0.033*	0.004	0.135
Space inside the Bus					Average	-0.087	0.032*	0.002	0.323
Below Average	-0.054	0.028*	0.006	0.094	Less Crowded	-0.073	0.038*	0.023	0.029*
Average	-0.03	0.031*	0.048	0.025*					
Presence of Service Security personnel					No. of Observation		527		
Not Satisfactory	-0.221	0.024*	0.058	0.024*	Log-Likelihood (Null)			-718.96	
Below Average	-0.15	0.024*	0.002	0.502*	Log-Likelihood (Model)			-428.44	
Average	-0.172	0.024*	0.032	0.028*	Pseudo-R²			0.4041	
Good	-0.138	0.025*	0.016	0.035*	Significant levels are coded by *				

To examine the determinants of passenger satisfaction with bus station services by considering both observed and unobserved heterogeneity between respondents, the Random Parameter Ordered Probit Model (RPOPMP) was developed. The model was developed on 527 valid observations, and overall satisfaction came as the dependent variable, and other socio-demographic and safety-related factors as the independent variables. The computed values of log-likelihood indicate strong model performance, and the negative log-likelihood (null) was found to be -718.96, and the negative log-likelihood of the fitted model was significantly less at -428.44. This increment shows that the included explanatory variables significantly enhance the model's explanatory capability. The McFadden pseudo-R², 0.4041, is yet another confirmation of the strength of the model, indicating that around 40% of the variation in passenger satisfaction is explained by the included attributes, which represents an excellent fit for a discrete choice model of this kind. As it is observed, the demographic factors of the passengers, especially the age, have a statistically significant effect on the level of satisfaction. Data show that the younger and middle-aged age groups are more satisfied than the older age groups, suggesting that younger and middle-aged passengers can be more flexible and tolerate current service conditions. In travel class, the people who travel in Local, AC, Non-AC, Sleeper, and Business Class buses are also showing a lower level of satisfaction, with the Business Class providing the most significant dissatisfaction. Facilities regarding women's safety were one of the most determinant variables of

satisfaction among the variables that are related to service quality. Each of the categories included in this variable had negative coefficients, with the ‘not satisfactory’ category having the strongest negative effect on the diminution of satisfaction, hence the dire need to implement more gender-sensitive safety measures. The purchasing process of the ticket is also a factor that leads to high satisfaction. Those passengers who buy tickets at counters, or via mobile services and conductors, claim lower satisfaction, which proves that inefficiencies and gaps observed in the traditional and online ticketing systems can become the central factors of dissatisfaction with the services. Similarly, the physical state of the buses, which is quantified by the parameters of air-conditioning, lighting, functionality of the fans, among other operating parameters, has a significant negative effect when assessed as poor or below average, therefore, validating the importance of mechanical maintenance and comfort in determining overall satisfaction. Facility-related aspects, such as the condition of toilets and the physical space in buses, also have a lot of negative effects when rated negatively. Such results support the highly significant role of hygiene, comfort, and spatial sufficiency as determinants of passenger well-being. In addition, the safety-related issues, such as the presence and efficiency of the station security personnel, affect perceived satisfaction significantly. The same stations with a lack of security presence or low-trained personnel decrease the chances of passengers reporting a high level of satisfaction significantly. Similarly, the visibility and accessibility of station staff and passenger information counters were depicted to have significant effects; the more approachable the staff is and the less congested the information counters are, the higher the satisfaction rating. On the whole, the main factors influencing the satisfaction of passengers with the services of bus stations, defined by the Random parameter Ordered Probit Model, are the perceived quality of services, guarantees of safety, and the sufficient, but not excessive, adequacy of the infrastructure. The high value of pseudo-R² and the significant increase in the log-likelihood testify to the strength of the model, as well as the significance of the explanatory variables chosen. Such findings indicate that service enhancement focusing particularly on the safety of women, toilet, bus maintenance, and security enforcement can significantly increase the levels of user satisfaction and service quality perceptions. Also, the recent change in ticketing, reasonable control over the specific stops, and the increased visibility of the people in the station can be used as a combination to create a more orderly and passenger-friendly transport space in general.

Table 2: Average Marginal Effect Computation

Variable Pattern	Categories				Interpretation
	Not Satisfactory	Average	Good	Excellent	
Age					
18-35 Years	0.000	0.000	-0.032	0.032	Younger passengers are slightly less “Good” but more likely “Excellent”; overall, higher satisfaction.
35 – 60 Years	0.000	0.000	-0.043	0.043	Middle-aged passengers show a higher “Excellent” satisfaction probability.
Travelling Class					
Local Bus	0.000	0.000	0.132	-0.132	More likely “Good,” less likely “Excellent”; moderate satisfaction.
AC Bus	0.000	0.000	0.115	-0.115	Higher “Good,” lower “Excellent”; fairly satisfied but expect better.
Non-AC	0.000	0.000	0.128	-0.128	Increased “Good,” reduced “Excellent”; moderate comfort.
Sleeper Bus	0.000	0.000	0.131	-0.131	More “Good,” less “Excellent”; adequate but not

			1		outstanding.
Women's Safety Facilities	0.168	0.137	0.10 5	0.088	Strong positive impact across levels; better safety raises satisfaction.
Bus stop (Fixed or Random)					
Mostly at designated stops	0.000	0.000	- 0.03 3	0.033	Slightly less “Good,” more “Excellent”; structured stops improve service.
Sometimes anywhere	0.000	0.000	- 0.03 3	0.033	Small increase in “Excellent”; moderate effect on satisfaction.
Often anywhere	0.000	0.000	- 0.02 8	0.028	Minimal change; irregular stops slightly lower quality perception.
Toilet Facility	0.028	0.000	0.00 0	-0.03	Poor facilities increase dissatisfaction and reduce excellence.
Space inside the Bus	0.000	0.020	-0.02	0.000	Limited space lowers “Good” ratings; crowding reduces comfort.
Presence of Service Security personnel	0.057	-0.057	0.05 2	-0.052	Weak security increases dissatisfaction; strong presence boosts satisfaction.
Station Security	0.025	-0.065	0.00 0	0.064	Poor security lowers “Average” satisfaction; better security raises excellence.
Visibility of Station Staff	-0.0704	0.000	0.05 2	0.020	Visible and approachable staff enhance satisfaction levels.
Ticket Buying Method					
From the ticket counter	0.000	0.000	0.02 4	-0.024	Slightly less “Excellent”; possible inefficiencies.
Mobile app / online	0.000	0.000	0.03 3	-0.033	Slightly less “Excellent”; technical issues may exist.
From the bus conductor or after boarding	0.000	0.000	0.03 2	-0.032	Lower “Excellent”; informal process causes dissatisfaction.
Bus condition (AC-Fan-Light)	0.045	0.000	0.00 0	0.047	Poor condition raises dissatisfaction; maintenance improves satisfaction.
Passenger Information Booth	0.000	0.024	0.03 3	0.027	Accessible information increases satisfaction probability.

The Average Marginal Effects (AME) calculated from the Random Parameter Ordered Probit Model provides detailed insights into how each independent variable influences the probability of passengers being placed in different categories of satisfaction. Average Marginal Effects are used to measure sensitivity about outcomes of satisfaction, which relates more to quantifying probability changes in categories of satisfaction in response to a marginal change in service attributes. Stable trends in categories imply that the results are robust to variations in outcome thresholds. The findings show that age has a positive relationship, with younger and middle-aged passengers being more inclined to report ‘Excellent’ satisfaction, which may be explained by a higher adaptability and lower expectations of older passengers. However, travel class variables, including Local, AC, Non-AC, and Sleeper buses, have a high likelihood of ‘Good’ satisfaction but a lower probability of Excellent satisfaction, indicating that passengers consider the services as average but not excellent in bus types. Women’s safety facilities show strong positive marginal effects at all satisfaction levels, which once again proves the importance of safety in forming the perception of passengers. Improving such safety will be estimated to lead to a significant upward shift in satisfaction levels. Similarly, bus stop regularity has a positive impact; customers boarding at regular bus stops are a little more likely to

achieve the ‘Excellent’ level of satisfaction, which supports the importance of structured and well-organized boarding systems in improving the perceived quality of service. Conversely, there is a negative correlation of toilet facilities with satisfaction, whereby poor conditions have a significant impact on increasing dissatisfaction. Lacking internal bus space also leads to a lack of satisfaction and, therefore, the necessity of proper comfort and crowd control.

The aspects of safety and security become especially relevant. Security personnel, as well as the overall security of the station, have significant marginal impacts, and poor security triggers increased disillusionment and diminished the chances of attaining greater levels of satisfaction. All these effects support the idea that strong safety assurance has a direct effect on passengers’ trust and comfort. The presence of station staff and the effectiveness of passenger information booths are also consequential; higher visibility of staff and channels of communication, respectively, raise satisfaction levels in several categories. Conversely, inefficiencies in ticket purchasing methods, be it counters, mobile applications, or conductors, have a minor negative impact on the likelihood of achieving the ‘Excellence’ level of satisfaction, suggesting room for technological and procedural improvements in the ticketing process. Lastly, bus condition, that is, the functional facilities in the bus like AC, lights, fans, etc., has a positive impact on satisfaction when well-maintained, thus the need to continue having a high level of satisfaction is noted through the need to ensure buses are properly maintained.

To conclude, the AME results reveal that an increase in safety, comfort, and information-related features has the strongest positive effects on passenger satisfaction. Policy interventions focusing on enhancing women’s facilities, ensuring visible security, maintaining station hygiene, and strengthening digital reliability can collectively shift passengers from moderate to high satisfaction levels, thereby enhancing the overall quality of bus station services in developing urban contexts.

6. DISCUSSION

Findings that were made through the use of the Random Parameter Ordered Probit Model (RPOPM) support the fact that passenger satisfaction at the bus stations depends on a series of interdependent service characteristics, such as safety, comfort, and quality of information. In line with the available literature that advocates the significance of technical and functional quality, the model proves that the physical environment and operational practices are equally important in the perception of satisfaction. The strong model fit (Pseudo- $R^2 = 0.4041$) and the significant coefficients further suggest that passenger perceptions vary systematically across attributes and demographic groups, thus supporting the need to model heterogeneity in the analysis of public transport satisfaction.

Findings indicate that the most significant predictors of satisfaction are women's safety facilities, security at the station, visibility of the staff, condition of toilets, and condition of vehicles. Such results are in line with other past researchers who have identified safety and hygiene as critical factors of perceived quality in emerging urban environments. The coefficients of the attributes are positive and have significant statistical values with high levels of Average Marginal Effects, which means that even a slight improvement in these areas can significantly increase the chances of a higher level of satisfaction. On the other hand, the weak ticketing systems, space, and irregular halting habits demonstrate negative correlations with the notion of satisfaction and indicate structural services and administrative flaws in the large terminals in Dhaka. The AME analysis has given a practical understanding of these trends that show the most significant improvements in the upward movements between the average to good or excellent spectrum of satisfaction are made through improvements in the facilities for women and the presence of security. Similarly, increased lighting, more visible signage, and more convenient access to information desks are good provisions; thus, it is concluded that a high level of employee engagement and effective communication channels can go a long way towards fostering the user experience. These results support the theoretical assumption that passengers are very responsive to the characteristics that reduce uncertainty and discomfort when waiting and getting on board. Altogether, the outcomes confirm that the quality of services in the station can significantly change the attitude of passengers to the bus service, despite the lack of significant infrastructural growth. The heterogeneity in sensitivities in the various groups of passengers is captured by the fact that random parameters are involved, and this would help provide information

with much more detailed policy advice as compared to the traditional ordered models. This is the reason why the combination of the RPOPM and AMEs can combine both methodological rigor and policy relevance to translate the statistical findings into practical strategies to enhance satisfaction. In practical terms, investments in safety, sanitation, maintenance, and the visibility of the staff are a cost-effective and short-term way of increasing passenger satisfaction and strengthening the appeal of the public transport systems in emerging cities like Dhaka.

7. CONCLUSION AND POLICY IMPLICATIONS

This research used a Random Parameter Ordered Probit Model (RPOPM) combined with the Average Marginal Effects (AMEs) to examine how the bus station characteristics affected the satisfaction of passengers in Dhaka, Bangladesh. Results also support the role of satisfaction being largely controlled by the dimensions related to women's safety, comfort, and service management, security of the station, cleanliness of the toilets, the presence of staff, and the state of the vehicles being the primary predictors. The results are, however, to be viewed as specific to major urban terminals, but the modelling framework can be generalized to other environments, provided that local recalibration is done. The higher fit to the data (pseudo- $R^2 = 0.4041$) shows that all these variables are significant contributors to the variability in satisfaction. Also, there is a strong heterogeneity of the passenger perceptions that, by the RPOPM, is revealed, and the need to move beyond homogeneous policy formulations and user-specific sensitivities. This interpretation is supported by the AME outputs that measure the probability increment of targeted attribute improvements. The results indicate that the initiative to enhance passenger experience in urban bus stations requires a focused bundle of action plan measures. Both safety and security must be enhanced through gender-sensitive intervention as well as properly trained personnel to enhance the confidence of the users. The hygiene and maintenance are also in urgent need, as the aspects of toilets, lighting, and ventilation have a great impact on the perceived quality of the services. The unclear signage, the lack of operational support desks, and the attendance of staff by the system in an organized way should be improved to provide a convenient level of staff accessibility and information visibility to facilitate the establishment of confidence and support. Digital ticketing systems that are reliable and easy to use might reduce congestion and time wastage during the waiting process, whereas periodic inspection and maintenance programs might also help in ensuring that the quality of these services is maintained throughout the vehicles and services in the station. All these low-cost, high-yield interventions would generate quick improvements in user satisfaction, and the modelling framework that is adopted here is a useful transferable tool for other developing cities to assess, appreciate, and rank the qualities of services in their limited resource contexts.

8. DECLARATION OF USE OF AI

The authors confirm that the use of artificial intelligence tools was confined to linguistic refinement and grammatical improvement. No AI was used in the development of the research design, data collection, methods of analysis, or interpretation of the results. The authors conducted all the analyses using original datasets, a thorough literature review, and computational programming languages using Python and R, and the work is entirely original.

9. REFERENCES

- Aidoo, E. N., Agyemang, W., Monkah, J. E., & Afukaar, F. K. (2013). Passenger satisfaction with public bus transport services in Ghana: A quantitative approach. *Scientific Journal of Pure and Applied Sciences*, 2(3), 148–155.
- Ali, A. N. M. (2010). Measuring service quality of public transport in Bangladesh: A case study of passengers' opinions. *Journal of Bangladesh Institute of Planners*, 3, 45–56

- Beirão, G., & Cabral, J. A. S. (2007). Understanding attitudes towards public transport and private car: A qualitative study. *Transport Policy*, 14(6), 478–489. <https://doi.org/10.1016/j.tranpol.2007.04.009>
- Bolton, R. N., & Drew, J. H. (1991). A multistage model of customers' assessments of service quality and value. *Journal of Consumer Research*, 17(4), 375–384. <https://doi.org/10.1086/208564>
Cambridge University Press. <https://doi.org/10.1017/CBO9780511805271>
- Christoforou, Z., Cohen, S., & Karlaftis, M. G. (2010). Vehicle occupant injury severity on highways: An empirical investigation. *Accident Analysis & Prevention*, 42(6), 1606–1620. DOI: <https://doi.org/10.1016/j.aap.2010.03.019>
- D'Agostino, R. B. (2017). Tests for the normal distribution. In *Goodness-of-fit-techniques* (pp. 367–420). Routledge. Retrieved from: <https://www.taylorfrancis.com/chapters/edit/10.1201/9780203753064-9/tests-normal-distribution-ralph-agostino>
- De Oña, J., & De Oña, R. (2015). Quality of service in public transport based on customer satisfaction surveys: A review and assessment of methodological approaches. *Transportation Science*, 49(3), 605–622. <https://doi.org/10.1287/trsc.2014.0544>
- Dell'Olio, L., Ibeas, Á., & Cecín, P. (2011). The quality of service desired by public transport users. *Transport Policy*, 18(1), 217–227. <https://doi.org/10.1016/j.tranpol.2010.08.005>
- DMTCL. (2016). *Dhaka Urban Transport Network Development Study*. Dhaka Mass Transit Company Limited.
- Eboli, L., & Mazzulla, G. (2007). Service quality attributes affecting customer satisfaction for public transport. *Transportation Research Part A: Policy and Practice*, 41(3), 298–308. <https://doi.org/10.1016/j.tra.2006.09.011>
- Greene, W. H., & Hensher, D. A. (2010). *Modeling ordered choices: A primer*. Cambridge University Press. <https://doi.org/10.1017/CBO9780511845062>
- Hensher, D. A., Rose, J. M., & Greene, W. H. (2015). *Applied choice analysis* (2nd ed.). Cambridge University Press. <https://doi.org/10.1017/CBO9781139052220>
- Hensher, D. A., & Greene, W. H. (2003). Mixed logit models: State of practice. *Transportation*, 30, 133–176. <https://doi.org/10.1023/A:1022558715350>
- Hussain, I., Ali, D. R., Bukhari, S. H., Kumar, S., Faraz, A. A., & Burki, S. (2025). AI-ENHANCED INTEGRATION OF MULTIMODAL DATA FOR EARLY PREDICTION OF HEART FAILURE EXACERBATIONS IN HIGH-RISK GROUPS. *The Research of Medical Science Review*. Zenodo. <https://doi.org/10.5281/zenodo.15181126>.
- Khatun, R., Aditya, M. T., Rifaat, S. M., & Mahmud, R. (2025). A quantitative analysis of assessing passengers' satisfaction level of inter-city train services in Bangladesh. *Case Studies on Transport Policy*, 101477. <https://doi.org/10.1016/j.cstp.2025.101477>
- Mouwen, A. (2015). Drivers of customer satisfaction with public transport services. *Transportation Research Part A: Policy and Practice*, 78, 1–20. <https://doi.org/10.1016/j.tra.2015.05.005>
- Naik, B., Tung, L. W., Zhao, S., & Khattak, A. J. (2016). Weather impacts on single-vehicle truck crash injury severity. *Journal of safety research*, 58, 57–65. DOI: <https://doi.org/10.1016/j.jsr.2016.06.005>
- Nordfjærn, T., Simsekoglu, Ö., & Rundmo, T. (2014). The role of deliberate planning, car habit and resistance to change in public transportation mode use. *Transportation Research Part F: Traffic Psychology and Behaviour*, 27, 81–91. <https://doi.org/10.1016/j.trf.2014.09.012>
- Redman, L., Friman, M., Gärling, T., & Hartig, T. (2013). Quality attributes of public transport that attract car users: A research review. *Transport Policy*, 25, 119–127. <https://doi.org/10.1016/j.tranpol.2012.11.005>
- Sogbe, E., & Susilawati, S. (2025). Dissecting pedestrian behaviour in Ghana: a cluster-based analysis of safety and risk profiles. *International Journal of Injury Control and Safety Promotion*, 1-15. <https://doi.org/10.1080/17457300.2025.2551560>
- Train, K. (2009). *Discrete choice methods with simulation* (2nd ed.).
- Xie, S., Ji, X., Yang, W., Fang, R., & Hao, J. (2020). Exploring Risk Factors with Crash Severity on China Two-Lane Rural Roads Using a Random-Parameter Ordered Probit Model. *Journal of advanced transportation*, 2020(1), 8870497. DOI: <https://doi.org/10.1155/2020/8870497>