STRUCTURAL EQUATION MODELING APPROACH FOR ACCESSING PARATRANSIT SERVICE IN BANGLADESH

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ABSTRACT

Paratransit services play a critical role as the primary mode of passenger transportation in suburban areas of Bangladesh where formal public transit options are lacking. However, there exists a notable research gap concerning the assessment of Service Quality (SQ) specifically for these areas. Previous studies predominantly focused on Dhaka, the capital city. This research aims to address this gap by delving into the fundamental factors that impact the SQ of paratransit services in Bogura city, utilizing Structural Equation Modeling (SEM). A total of twenty-eight observable variables were identified, reflecting the distinct traffic dynamics of the city. Through the analysis of responses from 687 paratransit users gathered via a standardized questionnaire, these 28 variables were categorized into three latent variable groups: "Comfort and Amenities," "Service Reliability," and "Safety and Security" using Principal Component Analysis. Among these, "Service Reliability" emerged as the most influential factor in determining overall SQ, with "Obedience to traffic rules" identified as the most influential observable variable. This research provides valuable insights for transportation planners, operators, engineers, and policymakers, enabling the development of transportation policies that enhance paratransit services, particularly in cities with limited public transit options.

Keywords: *Paratransit; Service Quality; Structural Equation Modelling; Principal Component Analysis; Latent Variables.*

1. INTRODUCTION

Paratransit services are now an essential and important part of urban transportation system. They present a wide range of potential benefits, including last-mile connection, affordable transportation options, and an impressive ability to adapt to commuter needs.

For developing country like Bangladesh, the significance of paratransit services is paramount. In a multitude of cities across the country, the absence of a comprehensive public transportation infrastructure leaves paratransit as the sole mode of transportation for the majority of commuters. This dependence on paratransit is particularly common in many cities where there is a conspicuous lack of options for public transportation. Even in Dhaka, the capital city, where public transportation is available, paratransit services play a crucial role in meeting the transportation needs of the ever-growing urban population. About 72% of the households use paratransit for their regular travel in Dhaka city (Rahman, 2022). In Bangladesh, the paratransit options comprise two prominent categories: motorized options such as CNG, Leguna, Tempo, three-wheelers etc. alongside the non-motorized alternative represented by traditional rickshaws.

However, despite their pivotal role, paratransit services in Bangladesh face various challenges. It is critical to investigate these issues and examine the quality of service offered by paratransit providers in order to understand how they might be improved, particularly in areas where they are the lifeline of mobility. Much research has been conducted to evaluate the service quality of public transportation, with a particular focus on bus services. Hadiuzzman et al. (2017) employed Structural Equation Modeling (SEM) to examine the connections among 22 service quality (SQ) attributes, revealing that 'Commuting Experience,' 'Ticketing System,' and 'Punctuality and Reliability' were the three significant endogenous attributes, while among the exogenous variables, 'Service Frequency (daily),' 'Air Ventilation System,' and 'Commuting Period (weekdays)' held the utmost importance. Das et al. (2017) evaluated the overall performance of the bus network system in Dhaka Metropolitan city under different operating conditions, highlighting the significance of roadway geometry and the number of private cars as key factors affecting overall bus network performance, especially on rainy days. Fitness of Passenger Vessel and Catering Service are found to have greatest influence in overall SQ of marine passenger vessel users while working with 20 variables (Khan et al., 2018). There is still a significant research gap when it comes to assessing the quality of paratransit services in Bangladesh. A few studies have focused mostly on Dhaka, where paratransit services paratransit services serve as a supplement to the existing public transportation. Rahman (2022) conducted a study in Dhaka, Bangladesh, focusing on low-income working women's satisfaction with various service features of paratransit modes, utilizing Structural Equation Modeling (SEM) to identify key attributes affecting overall paratransit service quality (SQ), with results highlighting the significance of variables such as 'Security of goods' and 'Security of passengers' in positively influencing SQ.

To analyse the importance of service variables researchers, use various statistical techniques. The techniques for analysing SQ can be broadly classified in to two categories (Mazzulla and Eboli 2006). The first category of techniques includes methods of statistical analysis, such as quadrant and gap analysis, factor analysis, scattergrams, bivariate correlation, cluster analysis, and conjoint analysis, while the second category of techniques includes parameters estimation by modelling (Khan, 2016). Among them, structural equation model (SEM) has become more popular in the field of transportation engineering in recent years for its ability to model complex relationships between latent variables and observed variables simultaneously.

While alternative methods such as Multiple Regression Analysis, Factor Analysis, and Path Analysis, Logit or Probit models could have been considered, SEM was preferred for its capacity to handle latent constructs, account for measurement errors, and evaluate complex relationships within a single model. This research aims to explore the attributes that affect the SQ of paratransit utilizing Structural Equation Modeling (SEM) in the city of Bogura where public transport is totally absent.

2. METHODOLOGY

2.1 Selection of SQ Attributes in SE Models

A total of 28 observed Paratransit Service Quality attributes were selected first. Also, three unobserved latent variables were extracted through factor analysis. These observed and unobserved latent variables used to construct SEM model. In addition to extensive literature review to select the variables, focus group discussions (FDGs) were conducted with various academics, policy makers (e.g., Officials of Bogura Municipality), and individuals related to paratransit service operators.

2.2 Sample Collection

In order to gather data, questionnaire surveys were conducted at a number of locations across Bogura, including marketplace, educational area (EA), residential area (RA), and central business area (CBA). The questionnaire designed in close ended format consists of three parts. It started with an introductory part in which the respondents are asked about their age, occupation, educational qualification and monthly income. The second part asks about reasons for commuting, availability of own transportation, need for public transport, and paratransit service choices. In the third part the respondents were asked to rate their experience on five points Likert scale vary between 1 to 5 (1 is for "Very Poor" and 5 is for "Excellent") on the different attributes related to SQ. The questionnaire surveys were conducted in the month of April 2023 between the hours of 10 a.m. and about 4 p.m. The samples were collected through face-to-face interviews. The importance of the variables and the numerical scale were explained to the respondent before any interview. However, the interviewer was careful not to bias the response. The entire respondent was not very well aware of questionnaire activity. The interviewer tried to explain it in their native language, Bengali. But still it was very difficult for interviewer to make them understood what does this mean, especially in the middle of the road. So, it was a drawback of the questionnaire that is found out while conducting the survey.

SEM is a large sample technique (usually sample size >200) (Lei and Wu. 2007) and the sample size required is somewhat dependent on model complexity, the estimation method used and the distributional characteristics of observed variables (Kline 2005). As rules of thumb the ratio of sample size to the number of free parameters can be as high as 20 to 1 (Tanaka 1987) or as low as 5 to 1 (Bentler and Chou 1987) – although several published studies do not meet this goal. An initial goal of 1000 samples were set for the data collection process. The random data sample was only 850, though, due to commuters' unwillingness to participate, rush hour traffic, and other unanticipated circumstances. The remaining sample size after removing anomalies was 687.

2.3 Structural Equation Modeling (SEM)

SEM is useful to researchers as a multivariate technique combining regression, factor analysis, and analysis of variance to estimate interrelated dependence relationships simultaneously (Eboli and Mazzulla, 2007). This method has been widely used in variety of fields including social science, psychology, economics, education, engineering etc. SEM uses path diagrams to represent the relationships among variables graphically. In these diagrams, arrows indicate the direction of influence between variables, and the strength of these relationships is expressed as path coefficients.

The complete SEM model has two parts: the structural model and the measurement model.
Structural equations can be described by: $\eta = \beta\eta + \Gamma X + \zeta$ (1)
Measurement equations can be described by: $Y = \Lambda y + \varepsilon$ (2)
X stands for exogenous observed parameters.
Y stands for dependent parameters.
η stands for latent dependent parameters.
β stands for coefficients of the η parameters.
ζ stands for errors in the structural relationship between η and X
Γ stands for coefficients of the X variables in the structural relationship
Λy stands for coefficients of y on η

3. DATA ANALYSIS

3.1 Factor Analysis

Data were factor analysed using principal components analysis (PCA) with varimax rotation using the SPSS 22.0 package. Exploratory factor analysis, including both principal component analysis and common factor analysis, is a statistical approach that can be used to analyse interrelationships among a large number of variables and to explain these variables in terms of their common underlying dimensions or factors (Hair, 2019). The objective was to reduce the 28 variables into fewer numbers of underlaying factors. The Kaiser-Meyer-Olkin (KMO) measure value of 0.889 was found which suggests that the data is appropriate for factor analysis, and the correlations between the variables are strong enough to identify underlying factors. The Bartlett Test of Sphericity with χ^2 = 6061 and significance level, $P<0.001$ suggests data set are related to each other. Scree plots and eigen values greater than 1 were used to determine the number of factors in each data set (Churchill and Iacobucci, 2009). The commonly accepted criteria for retaining principal factors in factor analysis are that their eigenvalues must be greater than 1 and the cumulative variance explained by these factors must be more than 40% (Kaiser, 1960). From factor analysis results, seven factors were initially extracted with eigen value greater than 1 and five of which have cumulative variation greater than 40%. However, for relevance, it was deemed appropriate to retain only three factors. Additionally, variables with factor loadings greater than 0.4 in absolute value were the only ones that were considered factor representative. Typically, researchers consider loadings greater than 0.30 to be meaningful (Fabrigar et al., 1999).

3.2 Proposed SEM Model

The model was constructed with 28 endogenous observed variables and three endogenous latent variables (Table 1). The 28 endogenous observed variables are dependent on the three latent variables and these three latent variables are interrelated.

Table: SQ variables and their roles in the proposed SEM models

SL No	Attributes	Type	Notation
1	Fitness of vehicle	Endogenous	y_1
2	Seat condition	Endogenous	y_2
3	Ease of entry and exit	Endogenous	y_3
4	Personal space	Endogenous	y_4
5	Internal cleanliness	Endogenous	y_5
6	Noise inside vehicle	Endogenous	y_6
7	Temperature inside vehicle	Endogenous	y_7
8	Fare	Endogenous	y_8
9	Advantage compares to expense	Endogenous	y_9
10	Payment Easement	Endogenous	y_{10}
11	Driver behavior	Endogenous	y_{11}
12	Driving skill	Endogenous	y_{12}
13	Obedience to traffic rules	Endogenous	y_{13}
14	Concern for other road users	Endogenous	y_{14}
15	Availability of alternatives	Endogenous	y_{15}
16	Availability on week days	Endogenous	y_{16}
17	Availability on holiday	Endogenous	y_{17}
18	Availability in nighttime	Endogenous	y_{18}
19	On Route passenger picking	Endogenous	y_{19}
20	On-time performance	Endogenous	y_{20}
21	Delay in total journey time	Endogenous	y_{21}

Continued			
22	Trip denials	Endogenous	y_{22}
23	Speed of the vehicle	Endogenous	y_{23}
24	Long route performance	Endogenous	y_{24}
25	Security of passenger	Endogenous	y_{25}
26	Safety from road accidents	Endogenous	y_{26}
27	Security of goods	Endogenous	y_{27}
28	Women safety	Endogenous	y_{28}
29	Comfort and Amenities	Latent	η_1
30	Service Reliability	Latent	η_2
31	Safety and Security	Latent	η_3

For model building and estimation STATA 13 software is used, which employs most commonly used maximum likelihood (ML) estimation method to generate SEM structure. The structure of the proposed SE model is shown in Fig. 1. From the structure the following equations can be written. The overall SQ of paratransit:

$$Z = \mu\eta + \delta + \Lambda \quad (3)$$
$$y = \gamma\eta + \rho \quad (4)$$

And η in Equation (3) can be expressed as
:
$$\eta = \beta\eta + \xi \quad (5)$$

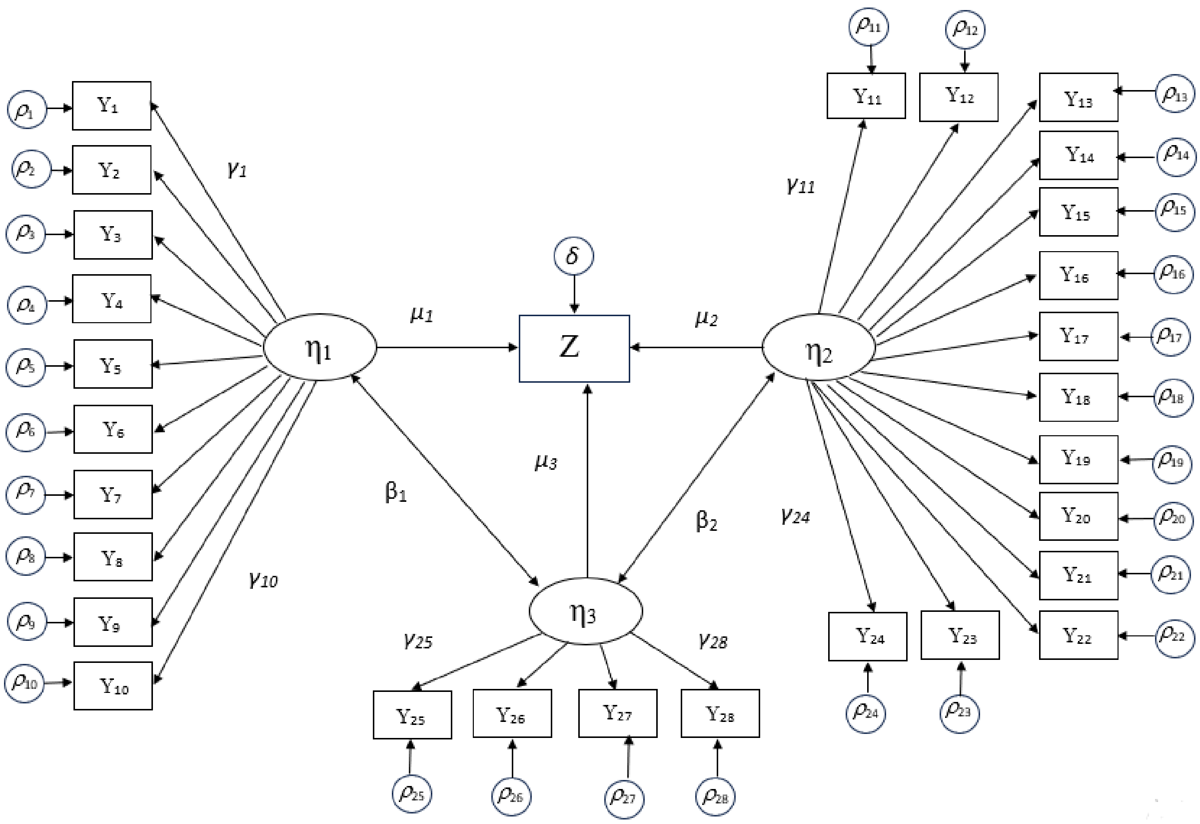

Figure 1: Path Diagram of SEM Model

4. EMPERICAL RESULT

A descriptive analysis was caried out from the response of the participants of the questionnaire which were recorded in numerical scale. In Table 2, general statistics of the data collected on numerical scale in questionnaire survey are shown. Among all the respondents, 2.74% rated the overall SQ of paratransit as very good, 10.98% rated it as good, 34.64% rated it as average, 37.75% rated it as poor, and 13.89% rated it as very poor.

In the proposed structural equation model, the observed variables are the 28 service quality attributes evaluated by the data set with a one global service quality indicators. The latent variables are the unobserved service quality aspects that can be explained through the observed variables. Factor analysis confirmed three latent variables. The first one is “Comfort and Amenities” related to attributes 1 to 10. The second latent variable “Service Reliability”, related to attributes 11 to 24 and the third latent variable “Safety and Security”, related to attributes 25 to 28. A two-tailed t-test with a critical value of 1.64 with a 90% confidence level was used to assess the significant values based on the coefficient values. These coefficient values were used to assess the model's acceptability by comparing it to the real-world scenario.

Table 2: SQ variables and their roles in the proposed SEM models

SL	Attributes	Mean	Standard Deviation	Skewness	Kurtosis	Numerical Scale
1	Fitness of vehicle	2.38	0.96	0.11	-0.8	1-5
2	Seat condition	2.63	0.96	0.11	-0.67	1-5
3	Ease of entry and exit	2.66	0.93	0.05	-0.54	1-5
4	Personal space	2.57	1	0.18	-0.61	1-5
5	Internal cleanliness	2.46	0.98	0.15	-0.63	1-5
6	Noise inside vehicle	2.13	0.95	0.71	-0.01	1-5
7	Temperature inside vehicle	2.23	0.96	0.5	-0.37	1-5
8	Fare	2.46	0.98	0.03	-0.73	1-5
9	Advantage compares to expense	2.47	0.94	0.18	-0.52	1-5
10	Payment Easement	2.6	0.87	-0.09	-0.32	1-5
11	Driver behavior	2.67	0.97	-0.04	-0.52	1-5
12	Driving skill	2.54	0.99	0.28	-0.35	1-5
13	Obedience to traffic rules	2.33	1.38	4.58	56.4	1-5
14	Concern for other road users	2.53	1.04	0.15	-0.57	1-5
15	Availability of alternatives	3.11	1.11	-0.12	-0.52	1-5
16	Availability on week days	3.76	1.11	-0.78	0.03	1-5
17	Availability on holiday	3.42	1.13	-0.43	-0.4	1-5
18	Availability in nighttime	2.7	1.06	0.31	-0.53	1-5
19	On Route passenger picking	2.25	1.33	1.78	9.56	1-5
20	On-time performance	2.38	0.98	0.33	-0.63	1-5
21	Delay in total journey time	2.54	0.93	0.32	-0.22	1-5
22	Trip denials	3.19	0.99	-0.17	-0.2	1-5
23	Speed of the vehicle	3.29	0.94	-0.21	0.21	1-5
24	Long route performance	2.57	0.93	0.23	-0.3	1-5
25	Security of passenger	2.38	0.96	0.33	-0.44	1-5
26	Safety from road accidents	2.14	0.9	0.68	0.32	1-5
27	Security of goods	2.3	0.97	0.41	-0.56	1-5
28	Women safety	2.20	1.06	0.54	-0.47	1-5

A multitude of indices were employed to evaluate the suggested model's goodness of fit. Table 4 lists the model's values for the Bayesian Information Criterion (BIC), Akaike's Information Criterion (AIC), Standardized Root Mean Square Residual (SRMR), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA). These numbers confirm that the model is acceptable. The goodness of fit assesses how accurate the relationship between the variables is and how useful the model will be in understanding and evaluating the Service Quality (SQ) of paratransit.

The result of the proposed model is shown in Table 3. Among the latent variable "Service reliability" is found to be most influential (coefficient 1.00). "Safety and security" is second (coefficient 0.559), followed by "Comfort and amenities" (coefficient 0.053). The positive coefficients indicate, they all affect the overall service quality (SQ) positively. The model also identifies the interrelation among the three latent variables. The analysis shows that "Comfort and amenities" and "Safety and security" affect (β_1=0.13; Table 3) each other. This means by ensuring the proper amenities, the safety and security of the commuters can be ensured as well. This also can be said that with improved security system and vehicular safety the commuter with feel better ease with the service. The analysis also shows the interrelation between the latent variable "Service reliability" and "Safety and security" (β_1=0.13; Table 3), highlighting that enhancing the safety and security system can contribute to an improvement in service reliability. This connection between safety measures and service reliability not only ensures a more secure travel experience for passengers but also reinforces the dependability of paratransit services, collectively enhancing the overall quality of service for commuters.

Table 3: Estimated parameter of SEM model for SQ of Paratransit

Variable Type	Name of the Variables	Coefficient	Z-value	P-value
Observed Variables	Fitness of vehicle	1.00	-	-
	Seat condition	1.317	10.612	0.000
	Ease of entry and exit	1.370	10.808	0.000
	Personal space	1.604	10.893	0.000
	Internal cleanliness	1.530	10.770	0.000
	Noise inside vehicle	1.280	9.829	0.000
	Temperature inside vehicle	1.291	9.778	0.000
	Fare	0.871	7.851	0.000
	Advantage compares to expense	1.056	9.098	0.000
	Payment Easement	0.984	9.198	0.000
	Driver behavior	2.042	3.597	0.000
	Driving skill	2.174	3.606	0.000
	Obedience to traffic rules	2.672	3.546	0.000
	Concern for other road users	1.292	3.305	0.001
	Availability of alternatives	0.378	1.688	0.091
	Availability on week days	1.171	3.175	0.001
	Availability on holiday	1.111	3.075	0.002
	Availability in nighttime	1.367	3.349	0.001
	On Route passenger picking	1.096	2.930	0.003
	On-time performance	2.620	3.629	0.000
	Delay in total journey time	2.537	3.649	0.000
	Trip denials	-0.557	-2.463	0.014
	Speed of the vehicle	0.388	1.982	0.047
	Long route performance	2.065	3.692	0.000
	Security of passenger	1.00	-	-
	Safety from road accidents	0.868	17.087	0.000
	Security of goods	1.044	18.670	0.000
	Women safety	1.140	18.909	0.000
Latent Variable	Comfort and amenities	0.053	0.491	0.623
		0.132[a]	6.855	0.000
	Safety and security	0.559	4.865	0.000
		0.113[a]	3.517	0.000
	Service reliability	1.00	-	-

[a]coefficient of latent variable while influencing another latent variable.

From the estimated model, the most influential observed variable is emerging to be "Obedience to traffic rules" (coefficient 2.672; Table:3). Bogura city, like many urban areas in Bangladesh, may face traffic congestion and safety concerns. That is why high obedience to traffic rules by paratransit drivers is crucial in such environments to ensure passenger safety, maintain smooth traffic flow, and contribute to an overall positive commuting experience. The model identifies "on-time performance" (coefficient 2.620; Table:3) as the second influential observed variable. This factor's high coefficient indicates that the timely arrival and departure of paratransit services significantly impact passenger satisfaction. Additionally, "delay in total journey time" (coefficient 2.537; Table:3) also shows high influence as delays can be particularly frustrating for commuters, impacting their daily routines. These two variables collectively reflect the city residents' awareness of time during their busy urban lives.

The traffic on the urban streets of most of the cities in Bangladesh can be charaterised as heterogenous mix traffic condition. This creates a challenge for the road users, specially for paratransit drivers to adopt in dynamic road context. Moreover, indiscipline in roads line illegal paring, frequent pedestrian crossing, vendor activities etc. which makes it more difficult to operate in road. A high coefficient for "driving skill" (coefficient 2.174; Table:3) suggests the passengers of paratransit have real concern for the issue as it directly influences their safety. The result also shows the observed variable "long route performance" (coefficient 2.065; Table:3) has a significant impact on the service quality of paratransit. As it is mentioned earlier that paratransit fill the gap created by the absence of public transport in Bogura city. Moreover, most people don’t have personal vehicle which they can to use for long route travel. The paratransit modes are the only affordable options for long route when bus or other options are not available. During political unrest or when all other modes of transport come to a halt, paratransit services play a crucial role in assisting passengers, navigating through local routes to ensure they reach their destinations. Some other influential factors: “Driver behaviour” (coefficient 2.042; Table:3), “Personal space” (coefficient 1.604; Table:3), “Internal cleanliness” (coefficient 1.530; Table:3), “Availability in nighttime” (coefficient 1.367; Table:3) and “Temperature inside vehicle” (coefficient 1.291; Table:3) which all have significant contribution to the overall service quality of paratransit in Bogura city. It is important to be mention that the variable "Trip denials"(coefficient -0.557; Table:3) implies that an increase in trip denials has an inverse effect on the service quality of paratransit in Bogura city. This suggests that instances where passengers are denied trips negatively impact the perceived quality of paratransit services and this perfectly match with the real scenario. Trip denials may lead to dissatisfaction among passengers, affecting their overall experience and perception of the reliability and accessibility of paratransit in the city. Addressing and minimizing trip denials could contribute positively to enhancing the service quality and user satisfaction of paratransit systems.

The variable "Availability of alternatives" (coefficient 0.378; Table 3) is the least influential factor in the proposed model. Even when a specific type of paratransit may not be readily available, the availability of other modes of transportation seems to have compensate the demand of the absence of a preferred mode. The real-life scenario also matches with the model observation.

The RMSEA value of the was found to be 0.093, which is within the prescribed value (Steiger, 1990). Though SRMR less than 0.10 indicates a good fit of the data in empirical SEM models (Vandenberg and Lance, 2000), the value was found in the proposed model is 0.105 which is slightly higher. Both CFI≥0.95(Hu and Bentler, 1999) and TLI≥0.95 (Sharma et al. 2005) indicates good fit. However, value of CFI and TLI are found 0.797 and 0.770. Though SRMR, CFI and TLI criteria do not meet the critical boundary value suggested by different authors but then again, while adopting the SEM approach, finding a poor fit is not that uncommon (Hooper, Coughlan, and Mullen, 2008). The model fit could be improved by reducing the number of parameters and then the number of observable variables explaining the latent variables.

Table 4: Goodness-of-fit measures of the proposed model

Fit indices	**Model Value**
Absolute fit indices	
Root mean squared error of approximation (RMSEA)	0.093
Standardized root mean square residual (SRMR)	0.105
Incremental fit indices	
Comparative fit index (CFI)	0.797
Tucker–Lewis index (TLI)	0.770
Continued	
Parsimony fit indices	
Akaike’s information criterion (AIC)	43615.371
Bayesian information criterion (BIC)	44012.249

5. CONCLUSIONS

This study aims to investigate influence of the factors that affect the service quality of the paratransit service utilizing Structural Equation Modeling (SEM) in the city of Bogura, Bangladesh. The Structural Equation Modeling (SEM) is an advance statistical technique which is used to analyse the complex relationships between observed and latent variables. In order to calibrate the model with 28 observed variables were selected with 3 latent variables confirmed by factor analysis. The model identified "Obedience to traffic rules" as the most influential observed variable that affect the SQ of Paratransit, followed by the factors "on-time performance", "delay in total journey time", "driving skill", "long route performance", “Driver behaviour”, “Personal space”, “Internal cleanliness”, “Availability in nighttime”, “Temperature inside vehicle” etc. Furthermore, the latent variable “Service reliability” has the highest impact on the SQ of paratransit. Upon identifying these factors, this paper certainly could help concern authorities to allocate limited resources to improve the service quality of this crucial service by prioritizing those factors based on their importance.

There are some limitations in this research. The effect of heterogeneity was not considered in this research, which certainly could affect the performance of the model. The sample size was relatively smaller compared to the number of variables and users. Also, the proposed models include insignificant variables considering complexity of the model but which have an effect on the model fit. Moreover, some results of factor analysis were ignored to maintain the feudality of the model with real life scenario.

These limitations create scopes for future researchers. In future larger data set and different SQ attributes should be included. Also, a comparative analysis can be carried out by calibrating variety of model with different data set from different cities.

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