IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

A STUDY ON CONSUMER PERCEPTIONS TOWARDS SERVICE QUALITY AND WAITING LINE IN AHMEDABAD'S BRTS NETWORK

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Abstract: This research paper investigates consumer attitudes towards Bus Rapid Transit Systems (BRTS) networks in Ahmedabad, India, employing factor analysis and discriminant analysis techniques. The study relies on primary data collected manually from a diverse sample of respondents. Through factor analysis, underlying dimensions influencing consumer attitudes are explored, providing insights into the factors driving perceptions of BRTS networks. Furthermore, discriminant analysis is employed to classify consumers based on their attitudes towards BRTS networks, facilitating a deeper understanding of the determinants of favourable and unfavourable perceptions. The findings of this study contribute to the literature on public transportation and urban mobility, offering valuable implications for policymakers, transit authorities and urban planners aiming to enhance the acceptance and effectiveness of BRTS systems.

Key words: Factor analysis, Discriminant analysis, Waiting line

I. INTRODUCTION

Bus Rapid Transit (BRT) systems are being set up in Indian cities with the goal of providing high-quality, contemporary rapid transit systems that offer quick, pleasant, cost-effective, and safe journeys to urban residents. Janmarg, commonly known as Ahmedabad BRTS, is a bus rapid transit system in Ahmedabad, Gujarat, India, established in 2009. Ahmedabad Janmarg Ltd operates 160 km of routes with 380 buses, serving approximately 2.20 lakh passengers daily [5].

Since its inception, the Ahmedabad BRTS has garnered attention for its innovative approach and effectiveness. However, the success of such systems is heavily dependent on the attitudes and perceptions of the consumers who use them. The state's job is not only to provide public transport services but also to assure their quality, resulting in passenger overall satisfaction.

This study aims to explore and analyse consumer attitudes towards the BRTS networks in Ahmedabad. By understanding the factors that influence user satisfaction, preferences and overall perceptions. Policymakers and planners can make informed decisions to enhance the service quality and encourage greater usage of BRTS. Through a comprehensive survey and analysis, this paper seeks to identify key determinants of consumer attitudes and provide actionable insights for the improvement of BRTS networks in Ahmedabad.

In this paper, we will examine various dimensions of consumer attitudes, including available of seats in the bus, crowd at station during peak hours, waiting line near ticket window, routes of buses, cleanliness at station, availability of buses, time it takes to reach the bus station and overall satisfaction. The findings from this study will contribute to the broader discourse on urban transportation planning and the role of BRTS in fostering sustainable urban mobility.

II. LITERATURE REVIEW

Tao, S. [8] (2015) presented three empirical investigations of interrelated travel behaviour dynamics of BRT passengers, providing an enhanced evidence base on which future BRT-related policy can be founded. Drawing on Brisbane (Australia) as the case study coupled with three distinct datasets (i.e., census, smart card and primary survey data). BRT passenger travel behaviour was investigated from three complementary perspectives, namely, modal share patterns of BRT catchments, spatial-temporal dynamics of current BRT usage and behavioural intentions of BRT passengers. Examinations from these three perspectives captured a broad spectrum of travel behaviour dynamics that collectively render a more holistic understanding of BRT usage.

Fahma, MR. [4] (2016) concluded that the current performance of BRT Trans Mamminasata affects its user satisfaction, in which time has the most significant effect to its user's satisfaction (Regression analysis). Furthermore, the variables used in the research, particularly the independent ones had been proved statistically as reliable ones. It was also aligned with the theories by Islam, et al. (Islam, Chowdhury, et al., 2014) who emphasized service, accessibility, and time as the underlying variables to measure the user's satisfaction of a bus service.

Cao, J. et al. [2] (2016) explored transit riders' satisfaction with bus rapid transit (BRT) and compared BRT with conventional bus and metro services using revealed preference data from Guangzhou, China. A tri-variate ordered probit model were developed to examine the effects of various service attributes on riders' overall satisfactions with the three types of transit. They found that the top-three influential attributes for satisfaction with BRT are ease of use, safety while riding, and comfort while waiting. Moreover, transit riders were most satisfied with metro, followed by BRT and conventional bus. The top-five attributes that contributed to the difference in the overall satisfaction between BRT and metro were ease of use, comfort while riding, convenience of service, travel time, and comfort while waiting. Based on the findings, they proposed specific strategies that can be used to enhance BRT quality of service.

Yanik, S. et al. [9] (2017) investigated the interrelationships among traveller satisfaction, travel and traveller characteristics, and service performance in a multimodal network that comprises of a trunk line and its feeder lines. They analysed the factors influencing the choices of access to rail transit stations and the satisfaction of transit travellers with the rapid rail transit systems and quantitatively studied these relationships and demonstrated the complexity of evaluating transit service performance. Since the interrelationships among variables affecting this system were mainly stochastic, they analysed the satisfaction with transit system problem using a Bayesian Belief Network (BBN), which helps capture the causality among variables with inherent uncertainty. Using the case of Istanbul, they employed the BBN as a decision support tool for policy makers to analyse the rapid rail transit services and determine policies for improving the quality and the level of service to increase the satisfaction with transit system.

Inturri et al. [6] (2021) propose to investigate the correlation among public transport (PT) use, user satisfaction, and PT accessibility using a spatial and statistical approach. They aim to find useful and simple indicators for sustainable mobility planning, focusing on a case study in Catania, Italy, with a specific emphasis on the mobility of university students. The authors highlight the implementation of fare-free PT for students from 2018 to 2020 as a collaboration between the University and urban PT operators. Their analysis is based on a database of approximately 4000 responses collected between 2018 and 2019, providing insights into the spatial and statistical correlations between user satisfaction, transit ridership, and accessibility.

Javida, M. [7] (2023) revealed that low satisfaction with transit modes has a negative impact on customers' behavioural intentions using factor analysis and structural equation. Also, he found that most of the respondents said that cost, travel time, air conditioning, travel time reliability, comfort, and ability to make stops on the way are very important attributes of the BRT services, moreover users believed that it will reduce air pollution, provide better accessibility, and would be safe for female travellers, customers' perceived level of importance significantly and positively influences their intentions towards BRT service.

III. DATA PREPARATION

3.1 Variables

Independent Variables: Availability of seats in the bus, Crowd at station during Peak hours, Waiting line near ticket window, Routes of bus, Cleanliness at station, Availability of bus, Time it takes to reach the Bus station.

Dependent Variable: Overall Satisfaction

Controlled Variable: Ahmedabad City

3.2 Hypothesis

Null Hypothesis:	The correlation matrix of Independent Variables is not suitable for factor analysis. (KMO Test)
Null Hypothesis:	The correlation matrix of Independent Variables is an Identity matrix, indicating that there is no significance correlation between all independent variables under study. (Bartlett Test)
Null Hypothesis:	There is no significant difference between overall satisfaction of travellers due to independent variables taken under study. (Wilks' Lambda)
Null Hypothesis:	The covariance matrix is equal across overall satisfaction of travellers due to independent variables taken under study. (Box's M Test)

3.3 Data Collection

Primary data has been collected through questionnaire from consumers who at least travel once through BRTS in route of Naroda to ISKCON BRTS station of Ahmedabad, Gujarat, India.

3.4 Sampling Technique

Non-probabilistic convenient sampling has been used to collect primary data where 300 observations were taken.

IV. METHODOLOGY

Factor Analysis: Factor analysis is a statistical method used to explore the underlying structure of a set of variables. It's commonly used in fields like psychology, sociology, and market research to identify patterns among observed variables and to reduce the complexity of data.

Discriminant Analysis: Discriminant analysis is a statistical technique used to classify observations into groups based on their characteristics or variables. It identifies which variables discriminate between the groups and creates a predictive model to assign new observations to the appropriate group.
Basic factor and discriminant analysis typically involve the following steps:

Factor Analysis	Discriminant Analysis
Data Collection: Gather data on a set of variables. These variables can be questionnaire items, test scores, or any other measurable quantities. **Correlation Matrix**: Compute the correlation matrix of the variables. This matrix shows how each variable is related to every other variable in the dataset. **Factor Extraction**: Use a factor extraction method to identify the underlying factors in	**Data Collection**: Gather data on predictor variables (also called independent variables or features) and the corresponding group or category each observation belongs to (the dependent variable). **Data Preprocessing**: Check for missing values, outliers, and ensure that the data meet the assumptions of discriminant analysis, such as normality and homogeneity of variance.

the data. The most common method is principal component analysis (PCA) or methods like maximum likelihood estimation (MLE). These methods aim to summarize the variation in the data with a smaller number of factors. **Factor Rotation**: After extracting factors, it's often helpful to rotate them to make them easier to interpret. Rotation methods like Varimax or Promax can be used to achieve this. **Factor Interpretation**: Examine the factor loadings to understand the relationship between variables and factors. Factor loadings represent the strength and direction of the relationship between variables and factors. **Factor Naming**: Based on the interpretation of factor loadings, assign names or labels to the factors that capture the underlying meaning or concept they represent. **Assessment of Model Fit**: Evaluate the overall fit of the factor model to the data using various fit indices. Common fit indices include the Kaiser-Meyer-Olkin (KMO) measure and the Bartlett's test of sphericity. **Interpretation and Reporting**: Finally, interpret the results of the factor analysis and report findings. This may involve discussing the identified factors, their interpretation, and implications for the underlying structure of the data.	**Variable Selection**: If you have many predictor variables, you may need to select a subset of variables that are most relevant for classification. Techniques such as feature selection or dimensionality reduction (e.g., PCA) can be used for this purpose. **Discriminant Function Estimation**: Estimate the discriminant functions that best separate the groups or categories in the data. These functions are linear combinations of the predictor variables and are determined based on the differences in mean vectors and covariance matrices between groups. **Model Assessment**: Evaluate the performance of the discriminant model using techniques such as cross-validation, ROC curves, or confusion matrices. This helps ensure that the model generalizes well to new data. **Prediction**: Once the discriminant functions are estimated and the model is assessed, you can use them to classify new observations into the appropriate groups or categories based on their values of the predictor variables. **Interpretation and Reporting**: Interpret the results of the discriminant analysis, including the discriminant functions, classification accuracy, and any insights gained from the analysis. Report findings in a clear and understandable manner.

Factor analysis is a powerful technique for understanding complex data structures and identifying underlying patterns or dimensions. However, it requires careful consideration and interpretation of results to ensure meaningful conclusions.

Discriminant analysis can be performed using various software packages (e.g., R, Python, SPSS), each offering different functions and capabilities for analysis and interpretation. It's a powerful tool for classification tasks, such as predicting customer preferences, diagnosing medical conditions, or identifying patterns in market research data.

V. STATISTICAL ANALYSIS

5.1 Factor Analysis

Table 5.1.1: Correlation Matrix

Correlation Matrix								
Correlation	**Time it Takes to Reach the Bus Station**	**Behaviour of Staff**	**Availability of Bus**	**Cleanliness at Station**	**Routes of Buses**	**Waiting Line Near Ticket Window**	**Crowd at Station during peak hours**	**Availability of Seats in the Bus**
Time it Takes to Reach the Bus Station	1.000	.686	.471	.422	.551	.180	.042	-.007
Behaviour of Staff	.686	1.000	.580	.434	.503	.183	.045	.003
Availability of Bus	.471	.580	1.000	.428	.420	.162	-.024	-.051
Cleanliness at Station	.422	.434	.428	1.000	.327	.128	.005	.005
Routes of Bus	.551	.503	.420	.327	1.000	.154	.003	-.036
Waiting Line Near Ticket Window	.180	.183	.162	.128	.154	1.000	.747	.720
Crowd at Station during peak hours	.042	.045	-.024	.005	.003	.747	1.000	.914
Availability of Seats in the Bus	-.007	.003	-.051	.005	-.036	.720	.914	1.000

The values of each correlation between different independent variables should be greater than or equal to 0.3 which can be seen from the derived correlation matrix. One can see that the first five variables are highly correlated to each other and so are the last three variables.

Table 5.1.2: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.767
Bartlett's Test of Sphericity	Approx. Chi-Square	1351.503
	df	28
	Sig.	.000

A Kaiser-Meyer-Olkin (KMO) value of 0.6 or higher is considered as acceptable for factor analysis. In the given set of data KMO Measure is 0.767 which indicates the suitability of factor analysis. Here the probabilistic value for Bartlett's Test of Sphericity is also less than the significance level for 95% of confidence interval which also suggests the same as KMO Measure.

Table 5.1.3: Communalities

Communalities		
	Initial	Extraction
Time it Takes to Reach the Bus Station	1.000	0.688
Behaviour of Staff	1.000	0.722
Availability of Bus	1.000	0.576
Cleanliness at Station	1.000	0.430
Routes of Bus	1.000	0.531
Waiting Line Near Ticket Window	1.000	0.797
Crowd at Station during peak hours	1.000	0.923
Availability of Seats in the Bus	1.000	0.911
Extraction Method: Principal Component Analysis		

Table 5.1.3 gives information about the variation explained by each independent variables in the initial stage and after the extraction.

Table 5.1.4: Total Variance Explained

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.066	38.325	38.325	3.066	38.325	38.325	2.983	37.293	37.293
2	2.512	31.400	69.726	2.512	31.400	69.726	2.595	32.432	69.726
3	.707	8.833	78.558						
4	.564	7.046	85.604						
5	.497	6.217	91.821						
6	.298	3.727	95.548						
7	.273	3.413	98.961						
8	.083	1.039	100.000						
Extraction Method: Principal Component Analysis.									

Based on initial eigenvalues of each component, only two factors were extracted by the model. Total Variance explained by these two extracted factors is 69.726%.

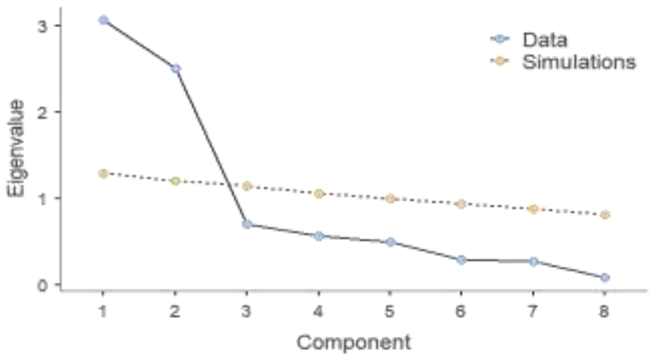

Figure 5.1.1: Scree plot

Graphical visualisation of extracted two factors with respect to its eigenvalues can be seen in the given scree plot (Figure 5.1.1).

Table 5.1.5: Rotated Component Matrix

Rotated Component Matrix[a]		
	Component	
	Transport Service Factor	Crowd Factor
Time it Takes to Reach the Bus Station	.828	.052
Behaviour of Staff	.848	.056
Availability of Bus	.759	-.004
Cleanliness at Station	.655	.025
Routes of Bus	.729	.014
Waiting Line Near Ticket Window	.195	.871
Crowd at Station during peak hours	-.023	.960
Availability of Seats in the Bus	-.067	.952
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.		
a. Rotation converged in 3 iterations.		

The rotation of factors improves the analyst's educated guesses. Varimax rotation is a statistical technique used at one level of factor analysis as an attempt to clarify the relationship among factors. Generally, the process involves adjusting the coordinates of data that result from a principal components analysis. Varimax rotation uses a mathematical algorithm that maximizes high- and low-value factor loadings and minimizes mid-value factor loadings.

5.2 Discriminant Analysis

0 denotes Satisfaction
1 denotes Dissatisfaction

Table 5.2.1 Group statistics

Group Statistics					
Overall Satisfaction		Mean	Std. Deviation	Valid N (listwise)	
				Unweighted	Weighted
0	**Transport Service Factor Score**	-0.6613312	1.00717752	124	124.000
	Crowd Factor	-0.7626907	1.05844894	124	124.000
1	**Transport Service Factor Score**	0.4659379	0.68362990	176	176.000
	Crowd Factor	0.5373503	0.46752692	176	176.000
Total	**Transport Service Factor Score**	0.0000000	1.00000000	300	300.000
	Crowd Factor	0.0000000	1.00000000	300	300.000

Table 5.2.1 denotes mean and standard deviation of two extracted factors for both groups in which the data is divided.

Table 5.2.2: Box's Test of Equality of Covariance Matrices

Test Results		
Box's M		118.273
F	Approx.	39.126
	df1	3
	df2	5295501.887
	Sig.	.000
Tests null hypothesis of equal population covariance matrices.		

Box's M Test used to test the homogeneity of covariance matrices. Its null hypothesis states that the covariance matrices are equal across groups. Higher the values of Box's M Test statistics higher the value of discriminant score is.

Table 5.2.3: Summary of Canonical Discriminant Functions

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	2.576[a]	100.0	100.0	0.849
a. First 1 canonical discriminant functions were used in the analysis.				

Eigenvalues represent the magnitude of the variability in the data along the principal components (linear combinations of the original variables). Eigenvectors represent the directions (or axes) of this variability. It tells about how much of the total variance in the data is accounted for by the discriminant function. Larger eigenvalues indicate more important discriminant functions, as they capture more of the variance in the data.

Table 5.2.4: Wilks' Lambda

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	Degree of freedom	Significance
1	0.280	378.466	2	0.000

Wilks' Lambda tests to identify overall difference between the groups. Null hypothesis of Wilks' Lambda tells that there is no significant difference between groups.

Table 5.2.5: Structure Matrix

Structure Matrix	
	Function
	1
Transport Service Factor Score	0.417
Crowd Factor	0.521
Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.	

Structure Matrix displays the correlation between each selected variable and each discriminant function. High absolute values of function indicates that the variable is highly correlated with the discriminant function and contributes strongly to group separation.

Table 5.2.6: Canonical Discriminant Function Coefficients

Canonical Discriminant Function Coefficients	
	Function
	1
Transport Service Factor	1.237
Crowd Factor	1.426
(Constant)	0.000
Unstandardized coefficients	

It displays the coefficients for each of the selected variables in each of the discriminant functions. Here value of intercept is zero and values for slopes related to Transport Service Factor and Crowd Factor is 1.237 and 1.426 respectively which can be written as:

$$\text{Overall Satisfaction} = 1.237x_1 + 1.426x_2$$

Here x_1 denotes Transport Service Factor and x_2 denotes Crowd Factor.

Now to represent the center of each group in the feature space, group centroids are derived which are the means of the predictor variables (features) within each group in discriminant analysis.

Table 5.2.7: Group Centroids

Functions at Group Centroids	
Overall Satisfaction	Function
	1
0	-1.906
1	1.343
Unstandardized canonical discriminant functions evaluated at group means	

These centroids of both groups can easily result into the threshold value to predict satisfaction level of new respondents. Here counts of respondents with no satisfaction and with satisfaction are 176 and 124 respectively and centroid values are given in above table. Threshold value calculated here is approximately zero $\left(\text{Formula: } T = \frac{n_1C_1+n_2C_2}{n_1+n_2}\right)$.

VI. RESULT

6.1 Factor Analysis

Correlation between the variables Time It Takes to Reach the Bus Station, Behaviour of staff, Availability of buses, Cleanliness of station, Routes of buses are very high and give maximum variation into first factor extracted. In same manner the variables like Waiting line near ticket window, Crowd at station during peak hours and Availability of seats in the buses are highly correlated to each other and contributes towards second factor.

Moreover, from table 5.1.3 it is visible that variables Waiting line near ticket window, Crowd at station during peak hours and Availability of seats in the buses explains maximum variation after the extraction of factors. These two extracted factors explain 69.72% of variation combinedly.

6.2 Discriminant Analysis

Value of Box's M test is very high in discriminant analysis and results into rejection of null hypothesis. It suggests that the groups generated on the basis of satisfaction and dissatisfaction from services of BRTS have different opinions for all the seven variables.

From table 5.2.1 it can be shown that crowd factor has maximum difference when the values of both the groups are compared. Even wilks' lambda suggests that there is significant difference between these two groups as its null hypothesis has been rejected.

Crowd factor has high absolute values of function compared to other factor which indicates that this factor is highly correlated with the discriminant function and contributes strongly to group separation.

The value of canonical correlation is **0.849**. The square of the canonical correlation is $(0.849)^2$ = **0.7208**, which means **72.08 %** of the variance in the discriminating model between Satisfaction and dissatisfaction is due to the changes in the seven predictor variables, namely, Time It Takes to Reach the Bus Station, Behaviour of staff, Availability of buses, Cleanliness of station, Routes of buses, Waiting line near ticket window, Crowd at station during peak hours and Availability of seats.

VII. CONCLUSION AND FUTURE SCOPE

Factor analysis helps in extracting two factors where crowd factor includes three variables related to crowd and queuing issue. In this primary data these three variables contribute the maximum suggested by factor analysis.

On other side, Discriminant analysis helps to give information about maximum variation into two groups of satisfaction and dissatisfaction which is due to crowd factor clearly seen from structure matrix. This primary study exclusively suggests that the variables like Waiting line near ticket window, Crowd at station during peak hours and Availability of seats are major issues related to the BRTS networks in Ahmedabad.

This study relies on primary data so its outcomes are trustable but the pilot data taken over here is comparatively less which can be extended in nearer future to find more accurate results. Furthermore, many other variables can be introduced in the study.

As this study suggest crowd factor and queuing as a major issue for Transit systems, one can surely do some widespread work in the field of queuing theory using mathematical modelling to solve the issues related to transit systems.

VIII. REFERENCES

1. Allen, J., Muñoz, J. C., & de Dios Ortúzar, J. (2020). On the effect of operational service attributes on transit satisfaction. Transportation, 47(5), 2307-2336.
2. Cao, J., Cao, X., Zhang, C., & Huang, X. (2016). The gaps in satisfaction with transit services among BRT, metro, and bus riders: Evidence from Guangzhou. Journal of Transport and Land Use, 9(3), 97-109.
3. Chaudhary, M. L. (2020). Commuters' perceptions on service quality of bus rapid transit systems: Evidence from the cities of Ahmedabad, Surat and Rajkot in India. Eur. Transp.-Trasp. Eur, 79.
4. Fahma, M. R., & Beenakker, I. BRT in Makassar (BRT Trans Mamminasata), Indonesia: Explaining the Effect of Current Performance to Its User's Satisfaction.
5. https://www.ahmedabadbrts.org/about-us/
6. Inturri, G., Giuffrida, N., Le Pira, M., Fazio, M., & Ignaccolo, M. (2021). Linking public transport user satisfaction with service accessibility for sustainable mobility planning. ISPRS International Journal of Geo-Information, 10(4), 235.
7. Javida, M. A., Tahirb, Q., Ammarb, M. M., Ahmad, B., Khanb, Y. M., & Alic, N. Customers' Satisfaction and Intentions with Public Transportation in Faisalabad, Pakistan: Implications for a Bus Rapid Transit Service.
8. Tao, S. (2015). Investigating the travel behaviour dynamics of bus rapid transit passengers.
9. Yanık, S., Aktas, E., & Topcu, Y. I. (2017). Traveler satisfaction in rapid rail systems: The case of Istanbul metro. International Journal of Sustainable Transportation, 11(9), 642-658.