

SERVICE QUALITY ASSESSMENT OF SHARED-AUTORICKSHAWS USING SUBSETS-BASED CONFIRMATORY FACTOR ANALYSIS

Lakhminarayanan SHANMUGAVEL^{1,*}, Chandrasekar PARSUVANATHAN²

¹ Research Scholar, Department of Civil Engineering, Hindustan Institute of Technology and Science, 603103, Chennai, India.

² Professor, Department of Civil Engineering, Hindustan Institute of Technology and Science, 603103, Chennai, India.

* corresponding author: rs.21701010@student.hindustanuniv.ac.in

Abstract

Shared mobility is changing urban transportation in India by providing transportation services without the need for ownership. Shared-autorickshaws (also called as share-autos) are a popular mode of shared mobility in the country. These informal vehicles can hold six to ten passengers and operate on a hail-to-board basis. It is important to evaluate the service quality of share-autos as they gain popularity. While research on passenger satisfaction with shared mobility services exists, studies on service quality perception related to share-autos are limited. To address this research gap, a survey was conducted with 581 share-auto users in India. The study created a Confirmatory Factor Analysis-based model with five latent variables and 22 manifest variables. The results revealed that 18 variables significantly influenced service quality. Variables that had weaker factor loading in the overall analysis were found more important when analysed for different subsets of the sample population. For instance, female-only or low-income-group respondents may prioritize different factors than the overall sample, and the ranking of factor loading changes across the subsets. The study shows that subset-based analysis can provide a more nuanced understanding of the passenger experience in share-autos, identifying potential opportunities to improve the quality of these services.

Keywords:

Shared-autorickshaws.
Share-autos.
Service quality.

1 Introduction

Shared mobility refers to a range of transportation services that allow people to share vehicles rather than owning them individually [1]. This can include ride-hailing services like Uber, Lyft, Baidu and Ola, bike and scooter sharing, and car-sharing programs like Zipcar [2,3,4,5]. In the case of ride-hailing services, passengers can request a ride and share a vehicle with other passengers who are headed in the same direction, while in the case of bike, scooter and autorickshaw sharing, multiple riders can use the same vehicle at any time. Shared mobility is becoming increasingly popular for several reasons, including its potential to reduce traffic congestion and carbon emissions, its convenience and affordability compared to traditional modes of transportation, and its ability to address issues like limited parking and last-mile connectivity. With the rise of digital technologies and the increasing focus on sustainable transportation, shared mobility is expected to continue to grow in popularity in the coming years [6, 7]. These vehicles resemble autorickshaws but are slightly larger. Shared autorickshaws (hereafter, 'share-autos' for brevity), typically carry six to ten passengers and can be either three-wheeled or four-wheeled.

Fig. 1 shows the difference between the appearance and design of autorickshaws and share-autos. Traditional autorickshaws operate on-demand, transporting passengers directly to their requested destination. In contrast, share-autos follow fixed routes but allow passengers to hail the vehicle by standing along the roadside and signalling the driver to stop and pick them up at any point along the way. While on-board, passengers can request the driver to stop the vehicle at any point along the route, and different passengers may exit at different locations. Share-auto services are available in major towns throughout India. Share-autos are informal and unregulated, and the pricing can vary

depending on factors such as time of day, traffic congestion, and demand. In the absence of formal regulation, pricing is often decided by the drivers based on the distance travelled. Despite challenges around pricing variability, safety, and regulatory compliance, share-autos contribute significantly to the mobility landscape in Indian cities.



Fig. 1: Comparison of autorickshaw and share-autos.

As share-autos become increasingly popular as a mode of transportation in the country, evaluating their service quality has become a critical concern for both small towns and urban areas. While there are broader studies that examine the factors impacting passenger satisfaction with shared mobility services in India, research focused on the perception of service quality of share-autos is limited. Although some studies are available on the service quality assessment of traditional autorickshaw services [6, 7], peer-reviewed research dedicated to share-autos is limited, presenting an opportunity for conducting this study. This represents a research gap that could be addressed to better understand the unique challenges and opportunities associated with this mode of transportation.

Assessing service quality can be a complex task given the subjective nature of user perceptions and the diversity of commuter preferences, as well as the wide range of service attributes involved. To address these challenges, researchers often turn to Confirmatory Factor Analysis (CFA), a powerful analytical tool that can help identify the underlying structure of service quality attributes and assess their relationships [8, 9]. CFA has been commonly used in this context, providing valuable insights into how different aspects of service quality impact user satisfaction, which can inform the development of targeted interventions to improve the commuting experience for share-auto users.

In studies that use CFA, it is common practice to remove or reject manifest variables that exhibit poor factor loading [10]. However, this approach does not account for the potential heterogeneity in the passenger experience and may overlook important factors that are significant for particular subgroups of passengers. This represents another research gap or opportunity that we address in our study. We are motivated by the hypothesis that variables showing poor factor loading in the overall analysis may become more important when analysed for homogeneous subsets of the collected data. For instance, what may not work for all respondents as a whole may work for specific subgroups, such as female-only or low-income-group respondents. By analysing such subsets separately, we can gain a more nuanced understanding of the passenger experience in share-autos, which can help identify opportunities to improve the quality of these services.

We administered a questionnaire survey with 581 share-auto users, using questions designed based on a construct of latent and manifest variables that we developed to quantify the underlying service quality attributes. To evaluate the proposed model, we performed CFA, which provided a basic understanding of the relationships between different service quality attributes. Subsequently, we conducted subset analyses that yielded more detailed insights into the service quality perceptions and preferences of the respondents.

Our study introduces a novel approach by demonstrating a grading system for analysing subsets of data. For example, if we analyse the service quality attributes for the entire sample of respondents, we may obtain a factor loading sequence of B-A-C for the manifest variables A, B, and C, respectively. Policymakers or decision-makers may use this information to prioritize service quality attributes. However, when we analyse the data for specific subgroups, such as the low-income group, the grading

of factor loadings could become A-C-B, indicating that the most important variables for this subgroup are different from those of the overall sample. Therefore, policymakers must verify the results at the subgroup level to ensure that investments are allocated to the most important variables that influence service quality.

The results of our subset-based analysis provided more nuanced insights into the factors that most significantly impact service quality for specific groups of passengers. These findings can assist service providers in developing targeted interventions to improve the commuting experience for share-auto users, which could lead to better satisfaction and increased usage of this mode of transportation.

2 Materials and Methods

2.1 Data Collection

After conducting a literature search, we determined that the essence of service quality could be captured through the following five categories of questions: convenience, comfort, economy, safety, and security. Accordingly, we framed the questions for our questionnaire survey to align with these categories. Each category included three to six questions, presented in statement form. For example, to gauge perceptions of fare, we directly asked respondents to indicate their level of agreement with the statement "the fare is reasonable" on a Likert scale ranging from 1 to 5 [11]. The use of a mandatory Likert scale minimizes the need for data cleaning. This scale measured the degree of agreement, with 1 representing "strongly disagree," 2 representing "disagree," 3 representing "neutral," 4 representing "agree," and 5 representing "strongly agree." The survey collected basic demographic information too, such as gender, age, income, and purpose of travel. In total, the questionnaire consisted of 24 questions/statements. Table 1 shows the categories, statement headings and the purpose of asking the opinion.

The primary construct here is the service quality of share-autos. It is considered a latent variable since it is difficult to measure directly. To develop the model, the five categories of questions are used to construct five latent variables with same names (convenience, comfort and so on). Table 1 shows them along with the statements presented to respondents to convey their perception via the 1-5 rating method. The statements or questions listed in Table 1 will become the manifest variables in the CFA model. These manifest variables are directly observable and can be measured through the survey. The reference headers listed in Table 1, such as "Payment Method" and "Delay at Terminals," are later used in the CFA analysis and serve as reference points for the analysis. These headers are referenced in subsequent tables and figures to provide context and clarity for the results of the analysis.

We selected a geographic area that was representative of a typical town in Indian states for the purpose of data collection. Salem (Fig. 5), a town located in the southern state of Tamil Nādu, was chosen due to its convenience for data collection. With a population of 1.17 million and an area of 124 square kilometres, Salem was an ideal setting for our study, as it was neither too urban nor too rural, allowing for a balanced representation of the population [12, 13]. The survey was conducted in January 2023, following pilot surveys that were carried out in November 2022. We administered surveys to share-auto passengers, share-auto drivers, share-auto owners, and members of the general public who did not use share-autos. It is important to note that the questionnaire used for share-auto passengers was different from the questionnaires used for other stakeholders. However, in this paper, we focus solely on analysing data collected from share-auto passengers to gain insights into their perceptions of service quality, as they are the primary stakeholders in this context. Another study utilizing data from the remaining stakeholders is currently in progress and will be published separately.

The questionnaire was created using a Google Form and distributed to a diverse group of 700 individuals, including students, working professionals, homemakers, and others, to ensure a range of economic backgrounds and ages were represented. A total of 581 responses were received, which is comparable to sample sizes of similar studies involving this population [8, 14 - 18]. Additionally, to include individuals who lacked access to the internet or did not own a smartphone, around 10% of the sample size was covered through oral surveys. The responses were not notably different to those obtained online, and therefore we did not pursue further oral questioning. Online respondents filled in the survey form within a week's time.

Table 1: Information about the questionnaire, reference headers and rationale.

Convenience	
Payment_Method:	Convenient to pay cash (fare) to the driver when alighting from the vehicle.
Delay_At_Terminals:	Drivers wait at the starting terminal until the vehicle is filled with passengers.
Travel_Time:	Travel time is affected by authorities conducting spot-checks.
Trip_Length:	Share-autos are generally used for short trips of a few kilometres.
All_weather:	Share-autos are suitable for both sunny and rainy days.
Comfort	
Crowding:	Drivers allow more passengers than the vehicle's capacity.
Suitable_For_Elderly:	Share-autos are suitable for elderly passengers.
Suitable_For_Luggage:	Share-autos have enough space to carry large luggage.
Cleanliness:	Share-autos are generally kept clean despite being shared with goods vendors.
Space:	Passengers sitting deep inside the vehicle find it difficult to get off.
Seating:	It can be comfortable to sit with strangers in share-autos.
Economy	
Fare:	The fare amount for share-autos is reasonable.
Relative_Fare:	The fare amount is reasonable compared to other modes of travel.
Cost_of_Access:	Share-autos can be accessed easily anywhere and anytime.
Safety	
Rash_driving	Drivers drive recklessly while trying to overtake other competitors.
Speed	Drivers drive faster to make more trips in a day.
Accident_Prone	Share-autos get involved in accidents.
Invehicle_pollution	Exhaust smoke circulate within the vehicle and cause health problems.
Injury_To_Legs	Limited leg space causes varicose problems.
Vehicle_Maintenance	Vehicles are poorly maintained.
Security	
Theft_phone	Strangers (co-travellers) might steal one's personal belongings.
Night_Time_Safety	It is safe to travel at night with strangers sharing the same vehicle.

Among 581 respondents, it was found that the number of males and females were almost equal with 293 and 288 respectively. The income groups are as follows: very low-income group (VLIG), low-income group (LIG), medium or middle-income group (MIG) and high-income group (HIG). The respondents classified into different income groups, with VLIG having 138, LIG having 267, MIG having 100, and HIG having 76, revealed that the age distribution was quite diverse with 131 of them being teenagers, 296 belonging to the young age group (less than 30 years of age), and 154 were categorized as older respondents. These findings suggest a well-distributed sample with a mix of both gender and age groups representing different income brackets.

Fig. 2 shows a detailed split of respondents under both male and female categories, for different income groups and different age groups. It seems most of the respondents are earning low income or very low income. A notable percentage of young, aged respondents is seen in these groups. (Fig. 3) shows the detailed split of respondents among various categories including trip purpose and mode choice. There is no single notable fashion or pattern seen, suggesting that there is a mixed proportions of respondents across the categories of gender, trip purpose and mode choice. 'Single-mode' refers to a situation where respondents use share-autos as the only exclusive mode for their trips; 'multi-mode' refers to use of share-autos as a part of multi-modal trip, perhaps for connecting to a bus, train, or other modes of travel. 'Random-choice' refers to the option where respondents choose share-autos as an exclusive mode one day, and perhaps use it as a part of multi-modal trip another day, purely on a random basis. This constitutes the major portion of respondents as per the split diagram shown. Another interesting observation there is that the shopping trips made by female in Salem city appears to be significantly higher than that of male. The data shown matches with our visual observation in the study area, and we were satisfied to proceed further with model construction, fitting, and analysis.

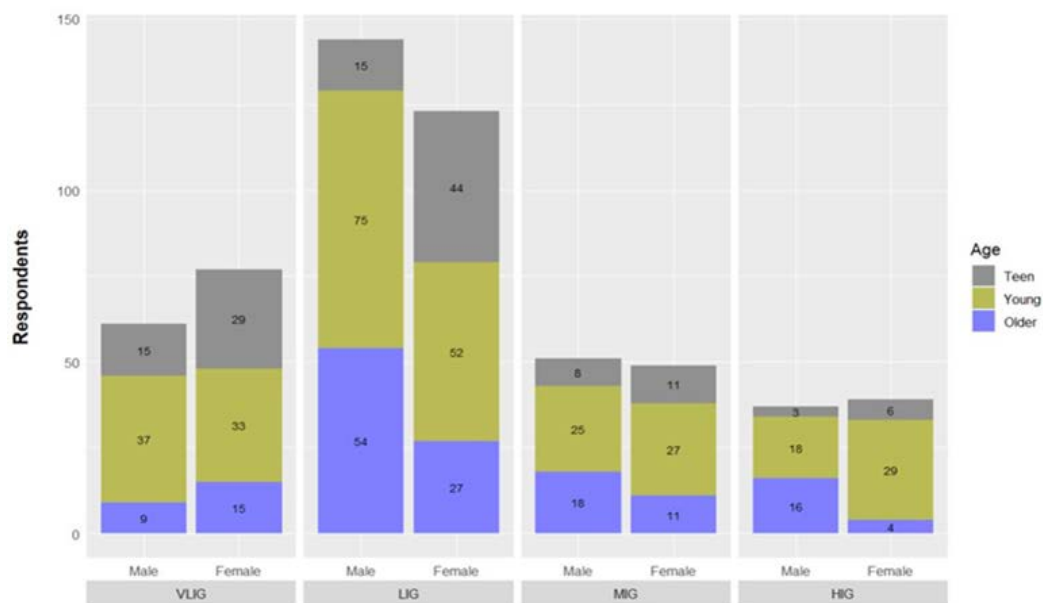


Fig. 2: Distribution of respondents based on income groups, gender, and age.

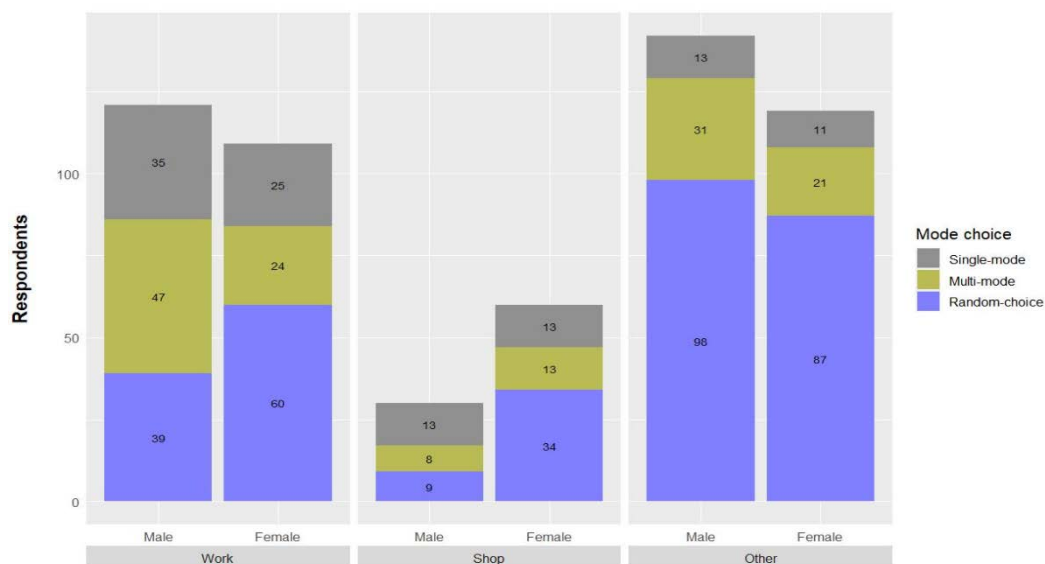


Fig. 3: Distribution of respondents based on trip purpose and the way share-auto is used.

2.2 Methodology

After collecting data through a questionnaire survey, the next step is to set up a model that includes all the latent and manifest variables. This is where we can start to apply confirmatory factor analysis (CFA) method, which allows us to better understand how different variables relate to one another and how they contribute to the overall construct of service quality [19, 20, 21].

Confirmatory factor analysis (CFA) is a statistical method used to test the validity of a measurement model that hypothesizes the relationships between observed variables and their underlying latent constructs. It is a commonly used technique in social sciences, psychology, education, and other fields where researchers aim to validate theoretical constructs using quantitative data [22, 23, 24].

Basic Mathematical Relationship:

In CFA, the relationship between the observed variables (y_j) and the latent variables (ξ_i) can be expressed as:

$$Y = \Lambda\xi + \epsilon \quad (1)$$

Where:

y – a vector of observed variables,

Λ – the factor loading matrix,

ξ – a vector of latent variables (factors),

ϵ – a vector of unique factors (errors).

Individual Parameters

• **Observed Variables (y):** These are the measured variables in the dataset. They are the manifest indicators that are presumed to be influenced by underlying latent factors.

• **Latent Variables (ξ):** These are unobserved variables that represent the underlying constructs or factors. They are hypothesized to influence the observed variables. In CFA, the goal is to confirm that the observed variables load onto the specific latent variables as predicted.

• **Factor Loadings (Λ):** This is a matrix that contains the coefficients (loadings) that link the observed variables to the latent variables. Each element λ_{ij} in Λ represents the expected change in the observed variable y_i for a one-unit change in the latent variable ξ_j . High loadings indicate that the observed variable is strongly associated with the latent variable.

• **Unique Factors (ϵ):** These are the error terms or unique variances associated with each observed variable. They represent the portion of the observed variable that is not explained by the latent variables. Each observed variable has a unique factor associated with it, reflecting measurement error and specific variance not accounted for by the latent factors.

Factor analysis has its roots in psychometrics and was first introduced by the pioneering psychologist L.L. Thurstone in the 1930s as a method for assessing the construct validity of psychological tests [25]. Since then, it has been widely used in a variety of fields to assess the validity of measurement instruments, confirm the structure of theoretical models, and test hypotheses about the relationships between latent variables. CFA has evolved over the years with the development of more sophisticated modelling techniques and software, and it continues to be a popular method for researchers who want to validate the structure of their data and test their theoretical hypotheses.

We utilized R programming and the Lavaan package to conduct confirmatory factor analysis (CFA) and evaluate the adequacy of our model fit and factor loadings [26, 27, 28]. Lavaan provides the option to analyse different subsets of data, either by treating the entire dataset as a single group or by specifying subsets using the 'group' parameter [29]. Alternatively, we could extract specific subsets of data from the main dataset using the subset function in R and analyse them as single groups using Lavaan. Both methods produced identical results in terms of factor loadings and model fitness, indicating that the choice between the two approaches is a matter of practical convenience.

The chi-square values, corresponding p-values, variances, and co-variances, as well as other statistics generated by Lavaan were found to be appropriate for the datasets used, with occasional misfits observed. For brevity, we present and discuss factor loadings in detail, but the same approach can be extended to other measures as well.

We prefer CFA over exploratory factor analysis (EFA) or structural equation modelling (SEM) for several reasons [30, 31, 32, 33]. First, CFA is more suitable when we have a pre-specified model with clear hypotheses about the relationships between variables. This is useful when we already have an idea of the underlying factors that contribute to a construct and want to test a specific model. EFA, on the other hand, is useful when we are exploring a dataset to identify underlying factors and do not have a pre-specified model. Second, CFA allows us to test the fit of our model to the data, which allows us to determine whether the hypothesized relationships between variables are supported by the data. In contrast, EFA does not test a specific model and instead generates a factor structure that best fits the data. Finally, while SEM is a more complex analysis that can test a variety of relationships between variables, it requires a larger sample size and more assumptions about the data than CFA. Overall, we prefer CFA for its ability to test a specific model and determine whether it fits the data.

3 Results

3.1 Factor loadings considering all-samples dataset

The model setup for confirmatory factor analysis is shown in Fig. 4. The numerical values displayed near manifest variables (headers) are factor loadings [34, 35]. We use actual factor loadings

instead of relative factor loadings. The latter is common where the first factor will get a loading of 1, and other factors will get relative loading values. However, our motive is to compare the results from subsets too; hence, we use actual loading values from the Lavaan output. Service quality, the main latent variable, and five sub-level variables are shown within elliptical shapes. There are two main types of model construction, namely reflective and formative [36, 37]. In a reflective model, the latent variable is conceptualized as causing or influencing the manifest variables. The manifest variables are seen as interchangeable indicators of the same underlying construct or factor. This means that the latent variable is thought to be responsible for the shared variance among the manifest variables. In a formative model, the manifest variables are seen as causing or forming the latent variable. This means that the manifest variables are viewed as independent indicators of the underlying construct, and the variance in the latent variable is explained by the manifest variables. Both reflective and formative models have their own advantages and disadvantages, and the choice between them should be based on the theoretical nature of the construct being measured, as well as the available data and research objectives. The literature shows that service quality models can be constructed as reflective models. Therefore, we assume that our model is constructed in a similar fashion and use the traditional method of drawing arrow marks that point from the main latent variable to the manifest variables.

The latent variable 'comfort' is linked to these manifest variables: perception on crowding, suitability for elderly, suitability for carrying big luggage, general cleanliness, space to manoeuvre inside the vehicle, and seating arrangement. All the variables showed factor loadings greater than 0.4, indicating that the construct is acceptable. The factor loadings ranged from 0.58 to 0.67 for the entire dataset considered as a single group. The highest factor loading was observed for space to manoeuvre, which is not surprising given that it can be challenging to alight from a share-auto if seated deep inside the vehicle. Exiting without physical contact with a stranger is not practical, and this factor seems to influence the comfort as expected.

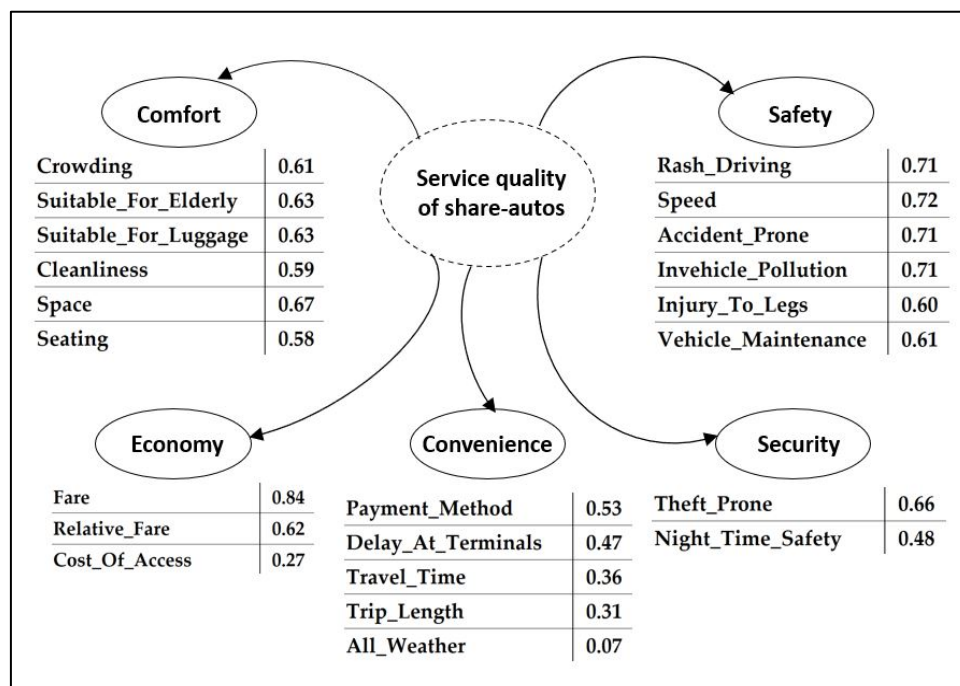


Fig. 4: Model setup and factor loadings.

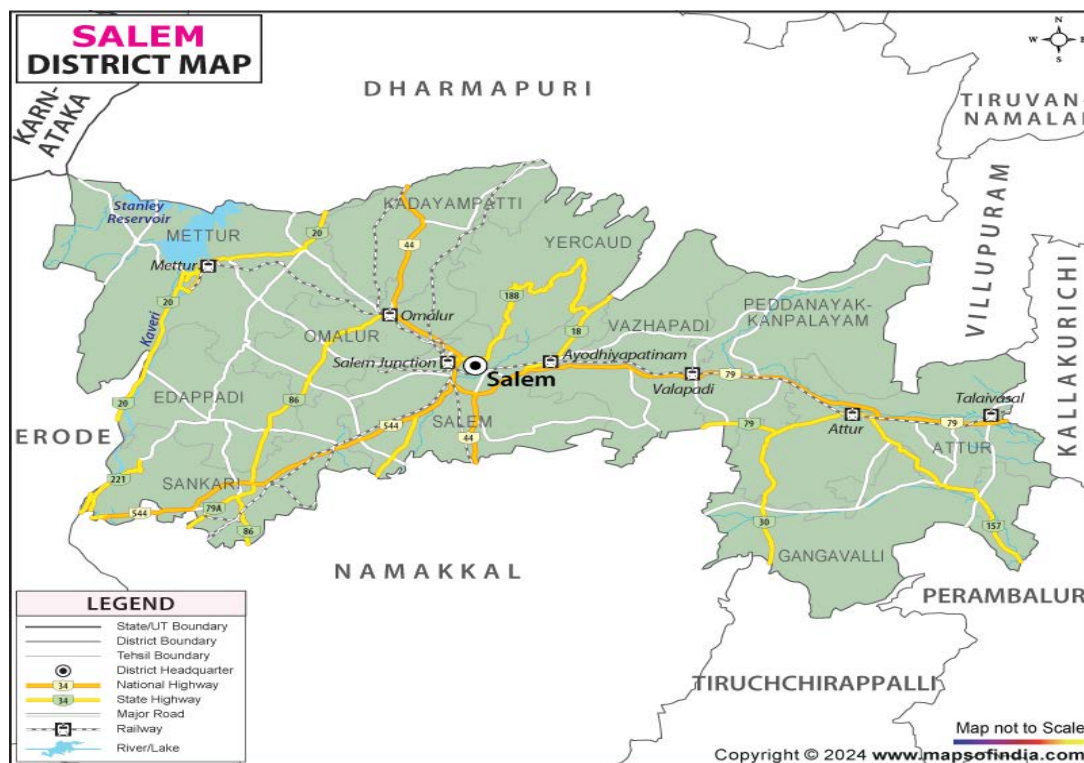


Fig. 5: Salem District Map.

To assess safety, six manifest variables were used: driving performance (indicating whether the driver drives recklessly), speed, the likelihood of getting into an accident, smoke and other exhaust circulating within the vehicle (which can cause asthma-related health issues), leg injuries (such as varicose veins), and general vehicle maintenance. The factor loadings ranged from 0.6 to 0.72, indicating a strong influence of safety measures. on the service quality of share-autos. Thus, safety proves to be a crucial aspect to consider while evaluating the service quality of share-autos, like any mode of transportation.

In terms of security, we considered two variables: the level of theft risk during travel (e.g., pickpocketing, chain-snatching) and the safety of traveling with strangers at night. The variable related to theft risk received a factor loading of 0.66, indicating a strong influence on the overall security of the service. Conversely, the variable related to safety during night-time travel with strangers had a factor loading of 0.48, indicating a moderate level of influence.

The marginal influence of night-time safety on security could be due to the limited number of respondents who travel at night. This could have affected their ability to form a strong opinion on the matter. Nevertheless, the high factor loading of 0.66 for theft-proneness indicates that this is a crucial aspect to consider when evaluating the security of share-autos. Policymakers should prioritize measures to improve the security of share-auto passengers, especially in terms of preventing theft-related incidents.

Convenience was found to have influence on service quality, with two out of five convenience variables having factor loadings greater than 0.4. Payment method and delay at terminals seem to influence the latent variable convenience. As such, to improve convenience for all passengers, decision makers could focus on improving these two aspects. For the method of payment, mobile apps or QR code-based payment methods could be considered. Terminal delay is caused by drivers who wait to fill the vehicle with passengers. This affects satisfaction of those already on board. Introducing a time-table could help alleviate this issue. Other manifest variables such as trip length or travel time and making the vehicle weather-proof did not appear to have a significant impact on convenience, probably due to the fact that it is obvious there is little scope for improving in these areas (in the study area considered).

We introduced a latent variable to consider economic reasons and linked it to fare, relative fare in comparison with other modes, and cost of accessing share-autos. Fare received the highest factor loading of 0.84, indicating that it strongly influences the economical aspect of service quality. The question of how good the fare is when compared to other modes received the second highest loading of 0.62. Surprisingly, the cost of access received only 0.27, despite being a major benefit of using share-

autos as they can be hailed and stopped at any location along the main road. Respondents weakly linked this variable, possibly due to a lack of clear explanation on how it affects the economy. This highlights the importance of clear communication in research studies. It also emphasizes the need for occasional refinement, even after exhaustive preparation and pilot studies. We have shared this issue in the discussion as a precautionary note for future researchers.

3.2 Factor loadings compared across subsets

Table 2 displays the factor loadings of a consolidated diagram, which employs colour coding and is convenient for visualizing the relationships between variables across 15 subsets and an all-samples dataset. The left side of the diagram shows the names of the five latent variables and their corresponding manifest variables, while the top arranges all the considered subsets. Each cell displays a factor loading value that corresponds to the manifest variable and its latent variable for any given sample set.

Instead of assigning a factor loading of 1 to the first variable and calculating the relative influence of the remaining variables, we use the actual factor loadings in our analysis. This approach allows us to rank or grade the variables, which is useful when comparing different subsets of the data.

The colour shading of the cell indicates whether the value under any subset is greater or smaller than the corresponding factor loading of the all-dataset value. If a value is greater, the cell is coloured yellow, while if it is smaller and drops below 0.4, the cell is coloured blue. There is a mixed effect on the factor loading for various subsets considered, with some showing an increase in factor loading value, while others show a decrease.

Different studies have presented varying threshold values for acceptable factor loading. In this study, a factor loading of 0.4 is considered the most common threshold to determine whether a manifest variable is influencing its parent latent variable [38, 39]. When considering the entire dataset, it was found that among the 22 manifest variables, four show poor relations with their parent latent variables. Specifically, under the "convenience" latent variable, travel time, trip lengths (provided by share-autos), and "all-weather" suitability (for share-autos during all seasons) exhibit poor factor loading to their parent latent variable. Additionally, the cost of access (i.e., expenses required to reach the road where share-autos are available) displays poor relations with the "economy" construct. One possible reason for such poor loading is that respondents may not relate or believe that these manifest variables are connected to the attached latent variable. In other words, there may be high variance in responses to the corresponding questions.

Prior to investigating into the benefits of subset analysis for gaining deeper understanding of constructs and their interrelationships, it is essential to first confirm the adequacy of the models tested across various subsets. To ensure the validity of any subset analysis, it is imperative to confirm the fitness of the models tested not only for the complete dataset but also for the subsets being considered.

Table 2: Factor loadings across subsets.

Latent variables	Manifest variables	All_Samples	Subsets or Groups														
			Gender		Income group				Trip purpose			Mode choice			Age		
			Male	Female	VLIG	LIG	MIG	HIG	Work	Shop	Other	Single-mode	Multi-mode	Random-choice	Teen	Young	Older
Latent variables	Samples (respondents) ->	581	293	288	138	267	100	76	230	90	235	110	144	327	131	296	154
	Proportion in % ->	100%	50%	50%	24%	46%	17%	13%	40%	15%	40%	19%	25%	58%	23%	51%	27%
Convenience	Payment_Method	0.53	0.67	0.39	0.48	0.57	0.44	0.57	0.49	0.50	0.63	0.63	0.55	0.51	0.59	0.57	0.20
	Delay_At_Terminals	0.47	0.41	0.59	0.40	0.42	0.67	0.45	0.49	0.62	0.44	0.55	0.33	0.49	0.51	0.45	0.83
	Travel_Time	0.36	0.43	0.30	0.57	0.40	0.16	0.24	0.31	0.39	0.39	0.43	0.25	0.38	0.41	0.41	0.20
	Trip_Length	0.31	0.23	0.44	0.25	0.30	0.28	0.36	0.44	0.42	0.20	0.36	0.17	0.38	0.31	0.36	0.32
	All_Weather	0.07	0.12	0.05	0.21	0.11	-0.12	-0.01	0.14	0.22	-0.05	0.31	-0.08	0.05	-0.05	0.14	0.05
Comfort	Crowding	0.61	0.65	0.59	0.63	0.61	0.67	0.50	0.68	0.54	0.60	0.66	0.51	0.65	0.61	0.64	0.53
	Suitable_For_Elderly	0.63	0.64	0.61	0.51	0.66	0.74	0.61	0.63	0.64	0.67	0.55	0.65	0.66	0.69	0.65	0.64
	Suitable_For_Luggage	0.63	0.68	0.61	0.55	0.70	0.70	0.37	0.62	0.49	0.69	0.70	0.59	0.63	0.71	0.62	0.54
	Cleanliness	0.59	0.65	0.53	0.67	0.59	0.51	0.66	0.62	0.50	0.60	0.69	0.48	0.61	0.63	0.62	0.49
	Space	0.67	0.63	0.72	0.67	0.66	0.63	0.73	0.69	0.60	0.65	0.72	0.67	0.64	0.72	0.69	0.50
	Seating	0.58	0.69	0.43	0.38	0.63	0.56	0.65	0.71	0.43	0.52	0.66	0.65	0.50	0.51	0.60	0.54
Economy	Fare	0.84	0.75	0.92	0.66	0.90	0.92	0.77	0.91	0.76	0.76	1.06	0.93	0.72	0.75	0.82	0.74
	Relative_Fare	0.62	0.75	0.53	0.74	0.59	0.44	0.80	0.57	0.63	0.73	0.57	0.67	0.61	0.55	0.71	0.62
	Cost_Of_Access	0.27	0.24	0.29	0.16	0.33	0.16	0.10	0.33	0.37	0.17	0.28	0.19	0.31	0.38	0.26	0.21
Safety	Rash_Driving	0.71	0.69	0.70	0.72	0.63	0.85	0.82	0.66	0.62	0.77	0.64	0.82	0.65	0.52	0.72	0.80
	Speed	0.72	0.70	0.72	0.71	0.70	0.74	0.83	0.74	0.60	0.74	0.59	0.78	0.72	0.72	0.72	0.74
	Accident_Prone	0.71	0.71	0.67	0.70	0.70	0.78	0.70	0.66	0.71	0.74	0.68	0.68	0.72	0.69	0.69	0.71
	Invehicle_Pollution	0.71	0.73	0.69	0.69	0.74	0.67	0.64	0.73	0.82	0.68	0.76	0.70	0.70	0.72	0.73	0.66
	Injury_To_Legs	0.60	0.61	0.62	0.58	0.65	0.57	0.49	0.69	0.70	0.52	0.82	0.66	0.50	0.61	0.66	0.48
	Vehicle_Maintenance	0.61	0.66	0.56	0.64	0.59	0.60	0.60	0.61	0.58	0.66	0.72	0.54	0.62	0.46	0.71	0.48
Security	Theft_Prone	0.66	0.70	0.56	0.60	0.50	0.89	0.99	0.69	0.64	0.54	0.93	0.44	0.65	0.66	0.60	0.89
	Night_Time_Safety	0.48	0.44	0.57	0.26	0.47	0.63	0.56	0.47	0.42	0.55	0.30	0.54	0.54	0.41	0.54	0.37

VLIG: Very low income group; LIG: low income group; MIG: middle income group; HIG: high income group

Note: Factor loadings for main and subsets of data. Yellow cells indicate an increase in the strength of the relationship between manifest and latent variables in comparison with all-dataset factor loadings, while blue cells denote instances where the manifest variables exhibit weaker associations with their corresponding latent variables than the all-dataset factor loadings.

3.3 Fitness of models

Model fitness refers to the degree to which the proposed CFA model fits the observed data. A good fit indicates that the proposed model accurately represents the underlying data, while a poor fit suggests that the model needs to be revised. There are several goodness-of-fit indices that can be used to assess the fitness of a model. In this study we use the most common indices, such as the root mean square error of approximation (RMSEA) [40-42], the goodness-of-fit index (GFI) [43,44], the adjusted goodness of fit index (AGFI) [45,46], the comparative fit index (CFI) [47,48] and the standardized root mean square residual (SRMR) [49,50].

A RMSEA value of less than 0.05 is considered good, while values between 0.05 and 0.08 are acceptable, and values between 0.08 and 0.1 are marginal [40-42]. For the GFI, AGFI, and CFI indices, values above 0.8 are considered good, while for the SRMR index, a value less than 0.08 is desirable [43-50].

Table 3 displays the fitness measures and values obtained from Lavaan output in R programming for CFA. Similar to factor loadings, different opinions exist regarding the necessary measures and corresponding values to determine a well-fitting model. The last row shows the overall level of fitness, with a value of 5 indicating a perfect model fit where all the fitness measures meet the criteria, and a value of 1 indicating that the model only barely passes for the subset under consideration. For further analysis, cases where at least 3 criteria are met will be considered.

The service quality model, comprising of five chosen latent variables and 24 manifest variables, exhibited a good fit with the all-sample dataset consisting of 581 samples. All five criteria were met in this case. Similarly, the model was also a good fit for both male and female subsets, with all five criteria being met. However, among the different income groups, only the LIG group (low-income group) demonstrated a good fit. For other income categories, the model exhibited a near-miss of the GFI and

CFI criteria with values above 0.7 but not exceeding 0.8. A similar pattern was observed for other cases, where the model fit closely but missed the criteria.

Table 3: Fitness measures and estimates.

Fitness measure	All Samples	Subsets or Groups														
		Gender		Income group				Trip purpose			Mode choice			Age		
		Male	Female	VLIG	LIG	MIG	HIG	Work	Shop	Other	Single-mode	Multi-mode	Random-choice	Teen	Young	Older
Size->	581	293	288	138	267	100	76	230	90	235	110	144	327	131	296	154
RMSEA	0.07	0.07	0.08	0.09	0.08	0.10	0.09	0.08	0.10	0.06	0.11	0.08	0.07	0.09	0.07	0.09
GFI	0.88	0.86	0.85	0.79	0.85	0.75	0.74	0.83	0.74	0.87	0.73	0.83	0.86	0.78	0.87	0.79
AGFI	0.85	0.83	0.81	0.73	0.80	0.69	0.67	0.78	0.67	0.83	0.65	0.78	0.82	0.72	0.83	0.73
CFI	0.83	0.84	0.81	0.73	0.81	0.75	0.78	0.81	0.69	0.86	0.72	0.81	0.82	0.74	0.86	0.70
SRMR	0.07	0.07	0.08	0.09	0.07	0.11	0.10	0.08	0.11	0.07	0.10	0.08	0.07	0.09	0.07	0.10
Fit level->	5	5	5	1	5	1	1	4	0	5	0	4	5	1	5	1

Note: Fit level refers to the number of criteria the model has met. A value of 5 indicates that the model has passed all five criteria. However, literature suggests that models can still be considered fit if they meet only two or three of the criteria, depending on the study conducted. Shaded cells are those cases where criteria are not met.

It is noteworthy to observe that the sample size may be a crucial factor influencing the subset's success or failure in terms of model fitness. The income groups' scenario exemplifies this, where the LIG subset with the highest number of respondents (267) performed best. Likewise, the trip-purpose group subset with the highest number of respondents (235) fit the model well, with only one criterion not being met in the subset with the next highest number of respondents (230). However, when the sample size drastically decreased to 90 for shopping trips, all criteria were missed, albeit with a near-miss. A similar pattern emerged in the mode-purpose group where the highest number of samples (327) passed all five criteria, and the subset with 144 samples passed four out of the five criteria. In contrast, the subset using share-autos as the only mode, with the lowest sample size (110), failed in model fitness. The young respondents' subset under the age group passed all criteria with the highest sample size (296). These results are in line with previous studies that underscored the importance of sample size. Further research with more extensive datasets could investigate the point at which a subset fails within a group. We will show how the subsets that passed can be used to make some important policy decisions, which might be missed if only a single group analysis of the entire dataset is considered.

4 Discussion

The constructed model, which includes service quality as a latent variable and five sub-level latent variables such as convenience, is found to be a good fit. The manifest variables show satisfactory factor loadings, except for a few cases. Our assumption that factor loadings might vary across subsets is confirmed, with some subsets demonstrating improved relationships with service quality while others do not. We test the same construct of latent and manifest variables with data subsets and confirm its fitness. Despite a reduction in individual subset sizes, results are mostly satisfactory. The benefits of using subsets are discussed here, including the ability to grade results and gain more insights into manifest variables within a latent variable.

Each latent variable can be analysed for how its manifest variables influence it across the subsets of data. Table 4 shows such a comparison. The latent variable considered here is 'comfort'. This is measured by six manifest variables. The values in the column under 'All' represents the grading of factor loadings for all-data set. Contents of Table 4 are derived from Table 3. Consider the six values for the 'comfort' latent variable in the 'All_Samples' column and corresponding rows. The highest value among these is assigned a grade A and shown in Table 4 in the corresponding spot, while the remaining values are graded accordingly. So, a value of 0.67 receives grade A for manifest variable 'space', 0.63 receives grade B (corresponding to elderly and luggage), and so on. Similarly, under the 'Male' column, the value of 0.69 for 'seating' is assigned grade A as it is the highest among that group. The same process is applied to derive all other values shown in Table 4.

Representing in this grade-format makes it easier to understand the influence rather than using actual factor loading values. Gender is represented by 'male' and 'female' subsets and income levels are represented as very low-income group (VLIG), low-income group (LIG), middle income group (MIG)

and high-income group (HIG) labels. Other subsets are not shown here just for brevity. What is explained here applies for all other subsets.

Table 4: Comparison of influence levels for the latent variable 'Comfort'.

Manifest variable	All	Gender		Income level			
		Male	Female	VLIG	LIG	MIG	HIG
Crowding	C	C	C	B	D	C	E
Suitable for the elderly	B	D	B	D	B	A	D
Suitability for big luggage	B	B	B	C	A	B	
Cleanliness	D	C	D	A	E	F	B
Space (inside vehicle)	A	E	A	A	B	D	A
Seating	E	A	E		C	E	C

Note: Factor loadings are graded according to their level of influence, with 'A' indicating the highest contribution, followed by 'B', 'C', and so on. Blank cells indicate poor factor loadings (i.e., those less than 0.4). Repeated values in a column indicate the same factor loading for different manifest variables.

Table 4 displays the manifest variables in the same order as they were asked to the respondents and is not sorted in any particular way. In the all-data set, denoted by the column heading 'All', the most influential factor for understanding the latent variable 'comfort' is the availability of space to board and exit the vehicle comfortably and move between seats, labelled as 'A'.

The sequence of values under the 'All' column is C-B-B-D-A-E. This sequence is generally expected to be the same for subsets as well, given a large enough sample size. However, in perception studies such as this, it is important to note that what is significant to one group may not hold the same value to another group, particularly in moderately conservative communities where shared mobility is a common practice.

For instance, the variable 'space' receives a grade of 'E' for the male group and 'A' for the female group. Our field observations suggest that men tend to board the vehicle without considering whether it is occupied by men or women, while women prefer to wait for a more gender-friendly vehicle that allows them to occupy a constrained space comfortably. This highlights the significance of considering subsets when making decisions based on such studies.

One more example is shown in Table 5, where variations in grades can be observed and analysed. We compare the grades of all-data with those of subsets based on gender and trip purpose to examine the latent variable 'convenience', using Table 5. Manifest variables are listed on the left side of the table. Notably, the manifest variable 'All_Weather' shows no significant influence across all subsets, as indicated by the blank cells. We removed this variable and conducted the analysis again, which yielded results similar to those already shown in the table. We included this variable back, to explore whether subsets exhibit a different influence, as demonstrated in Table 3. By focusing on instances where grade-A is evident, we can gain some valuable insights.

Table 5: Comparison of influence levels for the latent variable 'Convenience'

Manifest variable	All	Gender		Trip purpose		
		Male	Female	Work	Shop	Other
Payment_Method	A	A	C	A	B	A
Delay_At_Terminals	B	C	A	A	A	B
Travel_Time		B		C	D	C
Trip_Length			B	B	C	
All_Weather						

Note: Factor loadings are graded according to their level of influence, with 'A' indicating the highest contribution, followed by 'B', 'C', and so on. Blank cells indicate poor factor loadings (i.e., those less than 0.4). Three cases were 0.39, too close to 0.4, so included as italicized. Repeated values in a column indicate the same factor loading for different manifest variables.

It's noteworthy that the manifest variable 'Payment_Method' is receiving grade A in terms of factor loadings not only in the all-data set but also in most of the other subsets shown. However, unlike 'Payment_Method,' the manifest variables 'Travel_Time' and 'Trip_Length' did not show a factor loading of even 0.4 for the all-data set. Interestingly, the influence of these manifest variables is seen among some subsets (with grades B, C, or D), indicating that their importance may vary depending on the subgroup being analysed.

Subsets typically have much smaller sample sizes than the all-data set. Despite having a lower sample size, the above-said factor loadings in subsets improved. This highlights the importance of including subsets along with the entire sample set when analysing and understanding the model construct and its relationships.

A caution on grading the influences based on factor loadings. We use such grading for having a basic glimpse of how things turn across subsets. We could have directly used the 1-5 scale ranking obtained via survey to know how opinions vary across subsets. However, that involves variance analysis, co-variance analysis and other comparisons. In a way, doing those checks is indirectly implying that we are doing something similar to confirmatory factor analysis. Instead, it is easier to leave all those side-checks to CFA itself and use factor loadings for grading. Nevertheless, it must be noted that factor loadings are not purely intended for grading purposes; the magnitude of the factor loading depends not only on the scale of the manifest variable, but also on the variance of the manifest variable and the variance of the latent variable. The relationships between the manifest variables and the latent variable may not be independent of each other. This means that the effect of one manifest variable on the latent variable may be partly or fully mediated by the other manifest variables. This makes it difficult to determine the exact contribution of each manifest variable to the overall relationship with the latent variable. Additionally, if the subset of data is significantly different from the full dataset, for example if it has a different range of values or a different distribution, the factor loadings may also be different. As such, the grading demonstration should be taken as a possibility of learning the relationships at different subset-levels.

To confront these results with other studies:

- Most CFA-based studies in service quality assessment might set a higher threshold for factor loadings (commonly >0.7) [10]. However, this study considered factor loadings greater than 0.4 to be significant [34, 35]. This difference in the threshold could lead to different insights being drawn compared to studies adhering to the higher benchmark. - The focus on subset-based analysis is a departure from many service quality studies that tend to evaluate data without differentiating between specific user groups. When compared to other research that interprets the factors impacting service quality homogeneously, this study provides a deeper understanding of diverse user experiences.

- Studies in other geographical regions or within different transport sectors might reveal distinct service quality attributes as priorities for passengers [38,39]. For example, research in more developed cities might find that technological factors such as digital ticketing services hold more weight, contrasting with the study where practical concerns like cost and convenience might be key.

5 Conclusion

Key findings from this study suggest that:

- Different subsets of the population, such as female-only or low-income groups, may prioritize different factors of service quality.

- A total of 18 out of 22 manifest variables were found to significantly influence the service quality of share-autos, implying a broad range of important factors.

- The study employed a grading system for analysing subsets of data which helped in understanding the needs of specific user groups, and thereby could guide more tailored improvements in service delivery.

Based on the results, analysis, and discussion presented in this paper, it is evident that service quality assessment can be improved by considering sub-groups or subsets of data. By doing so, a better understanding of the relationships between sets of underlying variables can be achieved. The service quality of share-autos was represented by twenty-four manifest variables grouped under five latent variables, with few exceptions. A questionnaire survey was conducted to obtain information from share-auto users about the importance they placed on statements covering manifest variables. In the absence of other readily available tools, policy makers and decision makers can use confirmatory factor analysis to investigate service quality.

It is crucial to note that sample size matters, especially when considering subsets. Thus, it is essential to ensure that every subset has enough samples before making significant investment decisions. Due to the limited sample size in this study, we only considered one level of subsets, such as gender or income level. However, future studies with larger sample sets could extend this analysis to multi-level or nested subsets, such as identifying a subset of female respondents who are of low income and use share-autos for last mile connectivity. In this way, targeted groups can be identified for investment and improvement of service quality from their point of view.

References

- [1] RAHIMI, A. - AZIMI, G. - JIN, X.: Examining Human Attitudes toward Shared Mobility Options and Autonomous Vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, 72, 2020, pp. 133–154. <https://doi.org/10.1016/j.trf.2020.05.001>.
- [2] KOTÉK, P. - KOVÁČ, M. - DECKÝ, M.: "The Skid Resistance Evaluation on the Long-term Monitored Road Sections" *Civil and Environmental Engineering*, vol.10, no.2, 2014, pp.66-72. <https://doi.org/10.2478/cee-2014-0013>.
- [3] SCHAEFER, C. - STELTER, A. - HOLL-SUPRA, S. - WEBER, S. - NIEHAVES, B.: The Acceptance and Use Behavior of Shared Mobility Services in a Rural Municipality. *Smart Cities*, 5 (4), 2022, pp. 1229–1240. <https://doi.org/10.3390/smartcities5040062>.
- [4] TURÓN, K. - CZECH, P. - TÓTH, J.: Safety And Security Aspects In Shared Mobility Systems. *SJSUT.ST*, 104, 2019, pp. 169–175. <https://doi.org/10.20858/sjsutst.2019.104.15>.
- [5] MENG, L. - SOMENAHALLI, S. - BERRY, S.: Policy Implementation of Multi-Modal (Shared) Mobility: Review of a Supply-Demand Value Proposition Canvas. *Transport Reviews*, 40 (5), 2020, pp. 670–684. <https://doi.org/10.1080/01441647.2020.1758237>.
- [6] HARDING, S. E. - BADAMI, M. G. - REYNOLDS, C. C. O. - KANDLIKAR, M.: Auto-Rickshaws in Indian Cities: Public Perceptions and Operational Realities. *Transport Policy*, 52, 2016, pp. 143–152. <https://doi.org/10.1016/j.tranpol.2016.07.013>.
- [7] Rahman, M. - Akther, M. S. - Recker, W.: The First-and-Last-Mile of Public Transportation: A Study of Access and Egress Travel Characteristics of Dhaka's Suburban Commuters. *Journal of Public Transportation*, 24, 2022, pp. 100025. <https://doi.org/10.1016/j.jpubtr.2022.100025>.
- [8] OBIRI-YEBOAH, A. A. - OWUSU-ANSAH, P. - ABDUL-AZIZ, A. R. - WOANGBAH, S. K. - ASAMOAH, J. N.: Modelling the Economic Impact of Rickshaw Transportation in Ghana: The Case of Kumasi. *Results in Engineering*, 15, 2022, pp.100517. <https://doi.org/10.1016/j.rineng.2022.100517>.
- [9] PRIYE, S. - MANOJ, M.: Passengers' Perceptions of Safety in Paratransit in the Context of Three-Wheeled Electric Rickshaws in Urban India. *Safety Science*, 124, 2020, pp. 104591. <https://doi.org/10.1016/j.ssci.2019.104591>.
- [10] DAGNALL, N. - DENOVAR, A. - PARKER, A. - DRINKWATER, K. - WALSH, R. S.: Confirmatory Factor Analysis of the Inventory of Personality Organization-Reality Testing Subscale. *Front. Psychol*, 9, 2018, pp. 1116. <https://doi.org/10.3389/fpsyg.2018.01116>.
- [11] JOSHI, A. - KALE, S. - CHANDEL, S. - PAL, D.: Likert Scale: Explored and Explained. *BJAST*, 7 (4), 2015, pp. 396–403. <https://doi.org/10.9734/BJAST/2015/14975>.
- [12] Salem, India Metro Area Population 1950-2023. Available online: <https://www.macrotrends.net/cities/21392/salem/population> (accessed on 11 May 2023).
- [13] About Corporation. Available online: <http://www.salemcorporation.gov.in/about-corporation.php> (accessed on 11 May 2023).
- [14] HOSSAIN, M. - SUSILO, Y. O.: Rickshaw Use and Social Impacts in Dhaka, Bangladesh. *Transportation Research Record*, 2239 (1), 2011, pp. 74–83. <https://doi.org/10.3141/2239-09>.
- [15] DAS, D. - MANDAL, P.: Comparative Evaluation of Commuters' Preferences and Expectations for Sharing Auto-Rickshaw. *Case Studies on Transport Policy*, 9 (4), 2021, pp. 1567–1581. <https://doi.org/10.1016/j.cstp.2021.08.006>.
- [16] VAN VELDHOFEN, Z. - KONINCKX, T. - SINDAYIHEBURA, A. - VANTHIENEN, J.: Investigating Public Intention to Use Shared Mobility in Belgium through a Survey. *Case Studies on Transport Policy*, 10 (1), 2022, pp. 472–484. <https://doi.org/10.1016/j.cstp.2022.01.008>.
- [17] SCHAEFER, C. - STELTER, A. - HOLL-SUPRA, S. - WEBER, S. - NIEHAVES, B.: The Acceptance and Use Behavior of Shared Mobility Services in a Rural Municipality. *Smart Cities*, 5 (4), 2022, pp. 1229–1240. <https://doi.org/10.3390/smartcities5040062>.
- [18] HARTL, B. - HOFMANN, E.: The Social Dilemma of Car Sharing – The Impact of Power and the Role of Trust in Community Car Sharing. *International Journal of Sustainable Transportation*, 16 (6), 2022, pp. 526–540. <https://doi.org/10.1080/15568318.2021.1912224>.

- [19] KADAM, A. - BHALEKAR, G.: Prevalence of Carpal Tunnel Syndrome in Auto-Rickshaw Drivers. *Int J Health Sci Res*, 11 (8), 2021, pp. 35–44. <https://doi.org/10.52403/ijhsr.20210806>.
- [20] Shiftan, Y. - Barlach, Y. - Shefer, D.: Measuring Passenger Loyalty to Public Transport Modes. *JPT* 2015, 18 (1), 1–16. <https://doi.org/10.5038/2375-0901.18>.
- [21] TUAN, V. A. - VAN TRUONG, N. - TETSUO, S. - AN, N. N.: Public Transport Service Quality: Policy Prioritization Strategy in the Importance-Performance Analysis and the Three-Factor Theory Frameworks. *Transportation Research Part A: Policy and Practice*, 166, 2022, pp. 118–134. <https://doi.org/10.1016/j.tra.2022.10.006>.
- [22] DELZ, A. K. - GAYNOR, K. - O'CONNOR, R. - SCHMIEDER, L. - SOMERS, E.: A Confirmatory Factor Analysis of a Cognitive Model of COVID-19 Related Anxiety and Depression. *Acta Psychologica*, 234, 2023, pp. 103861. <https://doi.org/10.1016/j.actpsy.2023.103861>.
- [23] OLIVEIRA B. F. - SILVA, F. F. - CARVALHO, R. S. B. - VENTURA, R. V. - MATTOS, E. C. - FERRAZ, J. B. S. - ELER, J. P. - BALIEIRO, J. C. DE C.: Confirmatory Factor Analysis and Structural Equation Models to Dissect the Relationship between Gait and Morphology in Campolina Horses. *Livestock Science*, 255, 2022, pp. 104779. <https://doi.org/10.1016/j.livsci.2021.104779>.
- [24] WALTON, D. M. - NAZARI, G. - BOBOS, P. - MACDERMID, J. C.: Exploratory and Confirmatory Factor Analysis of the New Region-Generic Version of Fremantle Body Awareness—General Questionnaire. *PLoS ONE*, 18 (3), 2023, e0282957. <https://doi.org/10.1371/journal.pone.0282957>.
- [25] THURSTONE, L. L.: Multiple Factor Analysis. *Psychological Review*, 38 (5), 1931, pp. 406–427. <https://doi.org/10.1037/h0069792>.
- [26] WOLF, M. G. - MCNEISH, D.: Dynamic: An R Package for Deriving Dynamic Fit Index Cutoffs for Factor Analysis. *Multivariate Behavioral Research*, 2023, pp. 1–6. <https://doi.org/10.1080/00273171.2022.2163476>.
- [27] ROSSEEL, Y.: Lavaan: An R Package for Structural Equation Modeling. *J. Stat. Soft*, 48 (2), 2012. <https://doi.org/10.18637/jss.v048.i02>.
- [28] OBERSKI, D.: Lavaan. Survey : An R Package for Complex Survey Analysis of Structural Equation Models. *J. Stat. Soft*, 57 (1), 2014. <https://doi.org/10.18637/jss.v057.i01>.
- [29] BROWN, G. T. L. - HARRIS, L. R. - O'QUIN, C. - LANE, K. E.: Using Multi-Group Confirmatory Factor Analysis to Evaluate Cross-Cultural Research: Identifying and Understanding Non-Invariance. *International Journal of Research & Method in Education*, 40 (1), 2017, pp. 66–90. <https://doi.org/10.1080/1743727X.2015.1070823>.
- [30] WATKINS, M. W.: Exploratory Factor Analysis: A Guide to Best Practice. *Journal of Black Psychology*, 44 (3), 2018, pp. 219–246. <https://doi.org/10.1177/0095798418771807>.
- [31] GASKIN, C. J. - HAPPELL, B.: On Exploratory Factor Analysis: A Review of Recent Evidence, an Assessment of Current Practice, and Recommendations for Future Use. *International Journal of Nursing Studies*, 51 (3), 2014, pp. 511–521. <https://doi.org/10.1016/j.ijnurstu.2013.10.005>.
- [32] SCHREIBER, J. B. - NORA, A. - STAGE, F. K. - BARLOW, E. A. - KING, J.: Reporting Structural Equation Modeling and Confirmatory Factor Analysis Results: A Review. *The Journal of Educational Research*, 99 (6), 2006, pp. 323–338. <https://doi.org/10.3200/JOER.99.6.323-338>.
- [33] Jandačka, Dušan. "Sources of PM10 Air Pollution in Rural Area in the Vicinity of a Highway In Žilina Self-governing Region, Slovakia" *Civil and Environmental Engineering*, vol.11, no.1, 2015, pp.58-68. <https://doi.org/10.1515/cee-2015-0008>.
- [34] SHEVLIN, M. - MILES, J. N. V.: Effects of Sample Size, Model Specification and Factor Loadings on the GFI in Confirmatory Factor Analysis. *Personality and Individual Differences*, 25 (1), 1998, pp. 85–90. [https://doi.org/10.1016/S0191-8869\(98\)00055-5](https://doi.org/10.1016/S0191-8869(98)00055-5).
- [35] STEIGER, J. H.: When Constraints Interact: A Caution about Reference Variables, Identification Constraints, and Scale Dependencies in Structural Equation Modeling. *Psychological Methods*, 7 (2), 2002, pp. 210–227. <https://doi.org/10.1037/1082-989X.7.2.210>.
- [36] COLTMAN, T. - DEVINNEY, T. M. - MIDGLEY, D. F. - VENAİK, S.: Formative versus Reflective Measurement Models: Two Applications of Formative Measurement. *Journal of Business Research*, 61 (12), 2008, pp. 1250–1262. <https://doi.org/10.1016/j.jbusres.2008.01.013>.
- [37] HANAFIAH, M. H.: Formative Vs. Reflective Measurement Model: Guidelines for Structural Equation Modeling Research. *International Journal of Analysis and Applications*, 18 (5), 2020, pp. 876-899. <https://doi.org/10.28924/2291-8639-18-2020-876>.
- [38] SORTRAKUL, S. - INTHAJAK, M. - TRAKANSIRIWANICH, K. - UDOMRAKSASUP, P. C.: Tourism Experience Need For Local Food Tourism Activities Of Trang Province, Thailand. *International Journal of Early Childhood Special Education*, 14 (01), 2022. <http://dx.doi.org/10.9756/INT-JECSE/V14I1.194>.
- [39] WEN, C. - HU, F.: Investigating the Applicability of Alignment—A Monte Carlo Simulation Study. *Front. Psychol.* 13, 2022, pp. 845721. <https://doi.org/10.3389/fpsyg.2022.845721>.

- [40] SCHREIBER, J. B.: Core Reporting Practices in Structural Equation Modeling. *Research in Social and Administrative Pharmacy*, 4 (2), 2008, pp. 83–97. <https://doi.org/10.1016/j.sapharm.2007.04.003>.
- [41] MCDONALD, R. P. - HO, M.-H. R.: Principles and Practice in Reporting Structural Equation Analyses. *Psychological Methods*, 7 (1), 2002, pp. 64–82. <https://doi.org/10.1037/1082-989X.7.1.64>.
- [42] Korkmaz, H. - Fidanoglu, A. - Ozcelik, S. - Okumus, A.: User Acceptance of Autonomous Public Transport Systems (APTS): Extended UTAUT2 Model. *JPT* 2021, 23 (1). <https://doi.org/10.5038/2375-0901.23.1.5>.
- [43] ONA, J. - ONA, R. - EBOLI, L. - FORCINITI, C. - MAZZULLA, G.: Transit Passengers' Behavioural Intentions: The Influence of Service Quality and Customer Satisfaction. *Transportmetrica A: Transport Science*, 12 (5), 2016, pp. 385–412. <https://doi.org/10.1080/23249935.2016.1146365>.
- [44] KIM, B.-M.: The Structural Relationship between Exercise Passion, Sports Confidence, and Exercise Continuation Intention for Taekwondo Players: Moderating the Effect of the Coach's Support. *IJERPH*, 19 (23), 2022, pp. 15852. <https://doi.org/10.3390/ijerph192315852>.
- [45] DOLL, W. J. - XIA, W. - TORKZADEH, G.: A Confirmatory Factor Analysis of the End-User Computing Satisfaction Instrument. *MIS Quarterly*, 18 (4), 1994, pp. 453. <https://doi.org/10.2307/249524>.
- [46] KIM, Y. - LEE, S. - CHO, Y. - KIM, M.: Analysis of Causal Relationships for Nutrient Removal of Activated Sludge Process Based on Structural Equation Modeling Approaches. *Applied Sciences*, 9 (7), 2019, pp. 1398. <https://doi.org/10.3390/app9071398>.
- [47] DANG, H. L. - LI, E. - NUBERG, I. - BRUWER, J.: Understanding Farmers' Adaptation Intention to Climate Change: A Structural Equation Modelling Study in the Mekong Delta, Vietnam. *Environmental Science & Policy*, 41, 2014, pp. 11–22. <https://doi.org/10.1016/j.envsci.2014.04.002>.
- [48] KAARIAINEN, M. - KANSTE, O. - ELO, S. - POLKKI, T. - MIETTUNEN, J. - KYNGAS, H.: Testing and Verifying Nursing Theory by Confirmatory Factor Analysis: Testing Nursing Theory by CFA. *Journal of Advanced Nursing*, 67 (5), 2011, pp. 1163–1172. <https://doi.org/10.1111/j.1365-2648.2010.05561.x>.
- [49] Rodriguez-Valencia, A. - Ortiz-Ramirez, H. A. - Simancas, W. - Vallejo-Borda, J. A.: Understanding Transit User Satisfaction with an Integrated Bus System. *Journal of Public Transportation* 2022, 24, 100037. <https://doi.org/10.1016/j.jpubtr.2022.100037>.
- [50] KOTYUSOV, A. I. - KASANOV, D. - KOSACHENKO, A. I. - GASHKOVA, A. S. - PAVLOV, Y. G. - MALYKH, S.: Working Memory Capacity Depends on Attention Control, but Not Selective Attention. *Behavioral Sciences*, 13 (2), 2023, pp. 92. <https://doi.org/10.3390/bs13020092>.