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MODELLING AUTOMOBILE USERS' RESPONSE PATTERN IN DEFINING URBAN STREET LEVEL OF SERVICE

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Abstract. This paper presents a qualitative study on automobile users' response pattern to assess the provided transportation service quality under heterogeneous traffic flow conditions. An Automobile Users' Satisfaction index (AUS_i) is established using data sets of questionnaire survey collected from 34 urban street segments of three midsized Indian cities. About 977 respondents with a suitable cross-section of gender, age, driving experience etc. were participated in travellers' intercept survey. Rasch Model (RM) was applied to identify a set of quantitative measures to analyse the complex process of measuring perceived service quality and degree of drivers' satisfaction together. The present study comprehends the multidimensional nature of users' perception to evaluate AUS_i with the help of six-dimensional variables such as roadway geometry, traffic facilities, traffic management, pavement condition, safety and aesthetics. RM offers a particular score to each user and each dimensional attribute along with a shared continuum. This way, the attributes those are more demanding to produce satisfaction as well as the variation in response of different modes of transport are evidently identified. The key findings indicate that the participants reported lower satisfaction level mainly due to the absence of separate bike/bus pull-out lanes, improper parking facilities and interruption by non-motorised vehicles/public transit or roadside commercial activities. Fuzzy C-Means (FCM) clustering was applied to classify AUS_i scores into six auto Levels Of Service (LOS) categories (A–F) for each street segment. The model was well validated with a significant matching of predicted Automobile users' LOS (ALOS) service categories with the users' perceived Overall Satisfaction (OS) scores for fourteen randomly selected segments. This prediction model is new to mixed traffic flow condition, which uses linguistic information and real-life issues of drivers for the current state of services. Hence, the proposed method would be more credible than conventional models to support the decision makers for long term planning and designing road networks on a priority basis.

Keywords: urban street, level of service, perception survey, rating scale Rasch model, automobile users' satisfaction index, fuzzy *c*-mean clustering.

Introduction

Automobiles are the principal mode of transportation, meant for carrying persons as well as goods from one place to another on roadways in most of the day-to-day activities. Automobiles are often identified within a number of vehicle classes, including cars, motorcycles, autorickshaws, and Light Commercial Vehicles (LCVs) etc. as per the legal codes of respective country. However, modelling road service qualities from drivers' perspective have not been adequately explored so far under the influence of heterogeneous traffic flow conditions. In developing countries like India, drivers hardly follow any lane discipline in the mixed traffic flow environment because they have to share the through lanes mostly with non-motorized vehicles and heavy vehicles. Hence, the behavioural models for drivers in homogeneous traffic will fail to quantify the perceived satisfaction level of drivers under heterogeneous traffic flow conditions. Nowadays people are expecting faster, mobile and better class transportation facilities. With the aim of fulfilling the mobility demand and enhancing the delivered service quality, transportation agencies have to alter their services to satisfy the requirements of their prospective road users. To figure out the important factors reducing drivers' satisfaction level has been a vital concern for the transportation system in their efforts to preserve the road user's loyalty. Many latent models have been used to assess the behaviour of road user, but Rasch Model (RM) is distinctive from others by its fundamental statistical characteristics of incorporating psychological factors into the behavioural analysis. The proposed model in this study comprises six sets of multidimensional ele-

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ments (or latent variables) and each dimension contains a set of Quality Of Service (QOS) factors in themselves. Finally, Overall Automobile Users' Satisfaction (AUS_i) is considered as a resulting variable, derived from the consequence of six dimensional variables (geometrical features, traffic facilities, traffic management, pavement condition, safety and comfort, aesthetics).

An imperative source of information to know the performance of transportation system is the auto-user's satisfaction survey. The proposed model is grounded upon a simple idea that road attributes, which get poorer scores are more challenging to endorse than the attributes receiving higher scores. The assessment of the subjective feature is associated with the degree of user's satisfaction and the objective feature is associated with the quality of road attributes. The output being a simulated measurement of these two traits, Rasch (1980) assigns specified scores to each person (participant) or each item (attributes) along with a shared continuum. It is essential to note that the perceived quality and the degree of satisfaction were the collective outcomes of a complex process while dealing with the measurement of a provided transportation service. When looking to analyse this complex procedure of measuring both quality and satisfaction level, RM appears as particularly appropriate. This technique permits the identification of a set of quantitative measures those are free from any subjective as well as objective traits. This way, it is easy to evidently categorize the attributes those are more difficult to produce satisfaction and to identify the variations in response of different modes of transport.

The major objective of this research is to examine the QOS attributes significantly affecting the auto-user's satisfaction level and to suggest a way to integrate user's behaviour in the analysis of AUS_i. To accomplish the objective, the study methodology is divided into three sections. In Section 1, the classical RM is adapted to the context of QOS attributes provided by the transportation infrastructure. In Section 2, dimensional model is applied to evaluate the AUS_i. In the final Section, Automobile users' Level Of Satisfaction (ALOS) was calculated for each road segment and some remarks are highlighted, which will help in transportation planning to find out the base of improving the infrastructure.

1. Review of literature

An inclusive literature survey has been carried out in this study related to geometric and operational features of automobile mode of transport conducted by several researchers in the last few decades.

In US DoT (2003) research carried out an in-vehicle opinion survey of drivers based on road geometrical, operational and environmental conditions. The authors have arranged an inventory of 45 QOS factors identified by the drivers of urban arterial. Choo and Mokhtarian (2008) carried out a multivariate probit analysis by linking all the travel related strategy bundles i.e. travel maintaining, travel reducing, and major location change to various explanatory variables. The researcher recommended a significant number of variables and policy endorsements to moderate traffic congestion. Haustein (2012) suggested a mobility-related segmentation approach for elderly group and identified the determinants of mobility behaviour with the help of linear or ordinal regression analyses. The researcher delivered extensive facts about the diverse lifestyle, attitudes, travel behaviour, needs of the elderly, and the identification of preliminary points to decrease the car use. Faezi *et al.* (2013) applied logistic regression to forecast the overall performance level of motorcycles. The authors performed a video laboratory survey from three selected motorcycle lanes in Malaysia. The most influential factors perceived by the rider were found out as motorcycle volume, total lane width, pavement surface quality, and motorcycle speed.

Hummer *et al.* (2005) conducted video laboratory survey to evaluate LOS of shared use paths linking the traveller's perception to operational and geometric variables and revealed a strong correlation between path operation and Overall Satisfaction (OS) of the service quality. Flannery *et al.* (2008) developed a cumulative logit model to predict the service quality of automobile drivers' perception based on presence of median, landscaping, progression & posted speed limit. Deshpande *et al.* (2010) presented an alternative LOS analysis procedure for signalized urban street systems. According to Highway Capacity Manual (TRB 2010), the determination of urban street LOS is based on urban street classification and Average Travel Speed (ATS) on an arterial. However, the researcher proposed three approaches: Quality Of Progression (QOP), average delay, and ATS for more accurate assessment of LOS on an urban arterial.

Dowling *et al.* (2008) suggested the technique to predict traveller's perception of service quality on urban streets for different modes of transport namely auto, transit, bicycle and pedestrian. Four categories of LOS models were developed, one for each mode based on the traffic characteristics, intersection controls, and street cross-section. Shao and Sun (2010) categorized LOS into two parts: Level of traffic facility provided and Level of traffic operation. The researchers have reflected that the ratio of travel speed to Free Flow Speed (FFS) as an appraisal index of traffic operation. Mohapatra *et al.* (2012) applied a hybrid algorithm made of both Genetic Algorithm (GA) and Fuzzy C-Mean (FCM) clustering to define the ranges of six LOS categories. The authors have exposed the impact of physical and surrounding environmental characteristics of road segments while determining LOS. Patnaik and Bhuyan (2016) used an evolutionary algorithm, named Genetic Programming (GP) clustering to classify street and ranges of ATSs to define ranges of LOS categories (A–F) for mixed traffic flowsconditions. It was observed that the speed ranges corresponding to LOS categories in Indian context were lower compared to that was specified in Highway Capacity Manual (TRB 2010).

Table 1. Previous studies related to evaluation of QOS of road infrastructures

Authors	Input Variables and Study methodology	Findings
US DoT (2003)	Participants' driving experience based on a wide range of issues related to road environment were interviewed in focus group, In-vehicle and video- laboratory approach	Identified fourth QOS factors, important to automobile drivers regarding service quality on urban streets
Choo, Mokhtarian (2008)	Linking of travel maintaining, travel reducing, and major location change to various explanatory variables with the help of Multivariate probit analysis	Recommended a significant number of variables and policy endorsements to moderate traffic congestion
Haustein (2012)	Socio-demographic and attitudinal variables of elderly were examined with respect to their mobility behaviour using linear or ordinal regression analyses	Acknowledged extensive facts about diverse lifestyle, attitudes, travel behaviour, needs of elderly, and initial points to decrease car use
Faezi *et al.* (2013)	Participants' perceptions of comfort, convenience, safety, manoeuvrability, and operational characteristics of exclusive motorcycle lanes were studied using logistic regression	Found out the most important factors affecting riding quality are motorcycle volume, speed total lane width, and pavement surface quality
Hummer *et al.* (2005)	Traveller's perception scores for operational and geometric variables were recorded with the help of video-laboratory survey	Revealed a strong correlation among path operation and OS of service quality, while evaluating shared-use paths LOS
Flannery *et al.* (2008)	Set of explanatory variables, describing geometrical and operational effectiveness of urban street facilities were analysed using cumulative logit model	Predicted service quality of auto-drivers' perception based on presence of median, landscaping, progression and posted speed limit
Deshpande *et al.* (2010)	Average coordination adjustment factor, average delay and ATS were analysed using improved QOP assessment techniques	Derived alternative LOS analysis procedures for signalized urban street systems based on QOP, average delay, ATS
Dowling *et al.* (2008)	Variables related to traffic characteristics, intersection controls, street cross-section were analysed using stepwise regression technique and ordered probit analysis	Four LOS models were developed for each mode, i.e. automobile, transit, pedestrian and bicycle mode
Shao, Sun (2010)	The ratio of travel speed to FFS were analysed using Fuzzy set theory	Modified LOS concept into two parts: level of facility supplied and level of traffic operation
Mohapatra *et al.* (2012)	FFS and ATS were clustered in to number of groups using GA-Fuzzy clustering technique	Found lower ranges of FFS for different urban street classes and speed ranges for different LOS categories as compared to Highway Capacity Manual (TRB 2010) ranges
Patnaik, Bhuyan (2016)	FFS and ATS were clustered in to number of groups using GP clustering technique	Found difference in FFS and speed ranges for different LOS categories of Highway Capacity Manual (TRB 2010) ranges
TRB (2010)	Stops per mile and number of left turn lanes per intersection were considered in Ordered logit analysis to predict LOS	Ranges of six ALOS classes (A–F) were defined for urban street segments

The above literature reviews are summarized in Table 1, in which previous studies related to QOS, variables, study methodologies, and findings of their research are tabulated together.

From the above literature studies, it can be summarized that researchers mostly followed a quantitative way of determining service levels by the selection of speed-flow parameters as input variables. However, the role of drivers' behaviour in the estimation of LOS, vary extensively with variations in roadway geometry, vehicle composition, traffic operational conditions etc. under heterogeneous traffic flow conditions. Without including and understanding travel behaviour of different automobile users, it is impossible to integrate their need in the planning process of transportation system. Besides, any approach proposed by the transportation policy would be objectionable to the community when it will be implemented. In fact, in some behavioural models, OS of road drivers was taken into account for service level assessment, which is not the only parameter influencing road users' behaviour. It is also influenced by a group of auxiliary attributes with respect to different dimensions like geometrical feature, traffic management, safety etc. The present study figures out the multidimensional nature of users' satisfaction by investigating the psychological factors those influence drivers' riding quality to develop a novel and reliable ALOS models under the mixed traffic environment.

2. Methodology

To simplify the overview of the complete study framework, the steps followed to determine AUS_i and to develop the ALOS model has been specified in Figure 1.

2.1. Background of the research methodology

Item Response Theory (IRT) holds the principles of testing, design, analysis, and scoring of questionnaires. RM is the simplest model in IRT and used especially in the field of psychometrics to quantify both service attribute's difficulty as well as auto-user's ability along with a shared

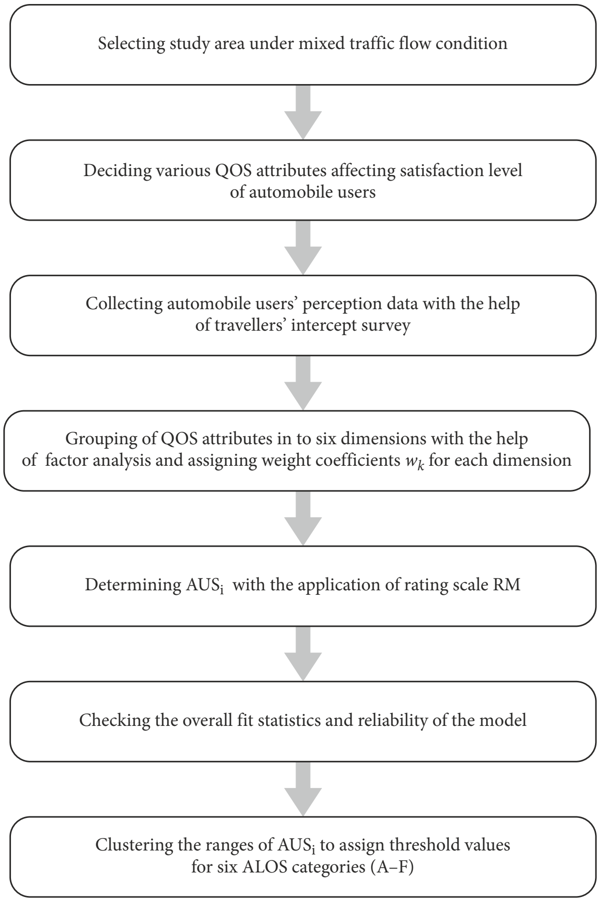

Figure 1. Overall study framework of ALOS model

continuum. De Battisti *et al.* (2005) specified that the response to a QOS attribute depends on two factors: first is the auto-user n's relative ability θ_n and second factor is the attribute i's intrinsic difficulty δ_i. Their relation is expressed by the difference $\theta_n - \delta_i$, which rules the probability of an answer. A positive difference indicates auto-user's ability is higher than the attribute's difficulty and the difference will be negative if the parameter δ_i seems more difficult to endorse than the user's need.

IRT started with the identification of the latent variable with an ability measure θ_n of auto-user (participant) n, and a difficulty of δ_i for QOS attribute i. Latent attributes are commonly discovered with the help of a questionnaire, which includes suitable QOS attributes to which participants can respond according to their riding experience. The response category in the survey questionnaire has incorporated ordered ratings (which varies from 5 – highly satisfied to 1 – highly dissatisfied) to represent a respondent's increasing inclination towards the concept questioned.

RM includes a particular structure in the response pattern i.e. probabilistic Guttman structure. Massof and Fletcher (2001) stated that, if attributes are systematically sorted from minimum difficulty to maximum difficulty, Guttman structure seems to be the most feasible response pattern for a respondent. If attribute's raw scores form one-dimensional ordinal scale, in which the attributes are ordered consistent with attribute raw scores and the automobile-users (auto-users') are ordered consistent with individual raw scores, then the data matrix will be fitted into a Guttman scale. Andrich (1978) mentioned that the response rating scale yields ordinal data, needed to be transformed to an interval scale, which is achieved by the rating scale RM.

2.2. Rasch model

To simplify the extended RM, initially, dichotomous responses are taken into consideration in which user's response is either "satisfied" (with a score of 1) or "dissatisfied" (with a score of 0)".

Now the probability P_{ni} that participant n will respond to a QOS attribute i with "satisfied" answer, is represented by the following relation:

$$P\left\{x_{ni}=1\middle|\theta_n,\delta_i\right\}=\frac{\exp\left(\theta_n-\delta_i\right)}{1+\exp\left(\theta_n-\delta_i\right)}=P_{ni}. \quad (1)$$

The probability that participant n will respond to a QOS attribute i with a 'dissatisfied' answer, is represented by:

$$P\left\{x_{ni}=0\middle|\theta_n,\delta_i\right\}=1-P\left\{x_{ni}=1\middle|\theta_n,\delta_i\right\}=\frac{1}{1+\exp\left(\theta_n-\delta_i\right)}. \quad (2)$$

The satisfied-to-dissatisfied ratio (also called as odds ratio) reflects the likelihood that user n is satisfied with QOS attribute i is explained as follows:

$$\frac{P\left\{x_{ni}=1\middle|\theta_n,\delta_i\right\}}{P\left\{x_{ni}=0\middle|\theta_n,\delta_i\right\}}=\exp\left(\theta_n-\delta_i\right). \quad (3)$$

Then, the participant and QOS parameters can be predictable from response odds ratios of the data set by taking logarithm of odds ratio (logit):

$$\ln\left(\frac{P\left\{x_{ni}=1\middle|\theta_n,\delta_i\right\}}{P\left\{x_{ni}=0\middle|\theta_n,\delta_i\right\}}\right)=\left(\theta_n-\delta_i\right). \quad (4)$$

Similarly, Andrich (1978) modified the RM to decompose a polytomous response into a number of dichotomous responses and to frame one rating scale problem into a number of binary-choice problems. It offers the value of attribute parameter δ_{ix} for rating category x to QOS attribute i. It also assumes that the probability of a user n answering with rating category x instead of $x-1$ to QOS attribute i is:

$$\ln\left(\frac{P_{nix}}{P_{ni(x-1)}}\right)=\left(\theta_n-\delta_{ix}\right). \quad (5)$$

The log odds of the probability that a user responds in category x for QOS attribute i compared to category $x-1$ is a linear function of user's perceived ability parameter θ_n and relative difficulty parameter (δ_{ix} for attribute i) of category x.

Andrich (1978) suggested two types of formulation for polytomous responses, widely accepted to evaluate the values of attribute and user parameters: Partial Credit Model (PCM) and Rating Scale Model (RSM). In PCM each attribute i has its specific threshold F_{ix} of individual category x. Therefore, $\delta_{ix} = \delta_i + F_{ix}$ for PCM. But in case of RSM: the rating scale is uniform for all QOS attributes i.e. each attribute has the same number of thresholds. The difference between any given threshold location and the mean of the threshold locations is invariant across attributes. Therefore, $\delta_{ix} = \delta_i + F_{ix}$ and Equation (5) becomes:

$$\ln\left(\frac{P_{nix}}{P_{ni(x-1)}}\right) = \left(\theta_n - \delta_i - F_x\right). \quad (6)$$

Hence, the RSM is derived as follows:

$$P\left\{x_{ni} = x \middle| \theta_n, \delta_i\right\} = \frac{\exp\left(\sum_{k=0}^{x}\left(\theta_n - \delta_{ix}\right)\right)}{\sum_{j=0}^{m}\exp\left(\sum_{k=0}^{j}\left(\theta_n - \delta_{ix}\right)\right)} = P_{nix}, \quad (7)$$

where: P_{nix} is the probability of choosing answer x for the attribute i by the user n; $\delta_{ix} = \delta_i + F_x$; F_x is the k-th threshold location of the rating scale, which is in common to all the QOS attributes; m is the maximum score, which is equal for all attributes.

2.3. Evaluation of AUS_i using dimensional RM

Earlier in Rasch analysis, it was noticed that the minimum values of δ_i parameter were associated with the QOS attributes with least difficulty (i.e. drivers have a higher value of probability of satisfaction for that attribute). Whereas, greater values of δ_i shows the higher probability of overcoming the difficulty of QOS attributes (results in less satisfied drivers). But in actual practice, some attributes with smallest values of δ_i parameter (which identify the QOS attributes of greater quality sometimes) also contribute to a lower value of OS for a particular road segment. Again, some QOS attributes with higher values of δ_i (which was expected to give lower satisfaction probability) correspond to average OS score. These kinds of problems occur, while the use of RM is confined to a single dimension in the context of assessing service quality or degree of satisfaction. According to Nicolini and Salini (2006) quality and user's satisfaction are multidimensional in nature composed of K number of dimensions. In order to get the unbiased satisfaction index, the interrelated QOS attributes were assembled into specific groups or dimensions and each dimension was independently analysed. RM was applied to each dimension to determine an OS coefficient for individual dimension, provided that the participants were same for every dimension.

The OS of all the independent dimensions have been combined in a suitable way: let there are K dimensions with continuous variables θ_k, each having n sets of individual coefficients for n number of automobile drivers. Then there will be $n \times K$ matrix of user satisfaction score θ_{ik} $(i = 1, 2, .., n;\ k = 1, 2, .., K)$. AUS_i was found out from a linear combination of θ_k variables and their respective weight coefficients w_k for each dimension. The dimensional variables considered in this model are correlated (not perfectly correlated). De Battisti *et al.* (2010) mentioned that the weight coefficients w_k for each dimension can be found out from factor analysis. The weight of linear combinations resulting from the factor analysis is given by:

$$w_k = \frac{\rho_{f_1,\theta_k}}{\lambda}, \quad (8)$$

where: ρ_{f_1,θ_k} – correlation coefficient between θ_k variables and the first factor f_1; λ – first eigenvalue of the correlation matrix.

Finally, individual user's satisfaction index AUS_i is explained by the following equation:

$$AUS_i = f_{1_i} = \sum_{k=1}^{K} w_k \cdot \theta_{ik}. \quad (9)$$

2.4. Model fit statistics

The degree to which responses satisfy the modelled expectations can be estimated with the help of fit indices. Bond and Fox (2003) recommended that the fit index can also assess "user's" as well as "attribute's" performance deviations from the "fit". Fit index is represented by either person fit (responses observed for each user on all attributes) or attribute fit (for each attribute on all users). In RM both the fit statistics are based on their standardized residuals. If X_{ni} is the perceived score of user n on QOS attribute i and P_{ni} is the probability of getting a correct response of user n on QOS attribute i, then the standardized residual Z_{ni} is defined as:

$$Z_{ni} = \frac{X_{ni} - E\left(X_{ni}\right)}{\left(\mathrm{var}\left(X_{ni}\right)\right)^{0.5}}. \quad (10)$$

Wright and Masters (1982) had derived that the fit index for attribute i can be derived by squaring Z_{ni} and summing over n. Similarly, fit index for user n can be derived by squaring Z_{ni} and summing over i. Bond and Fox (2003) suggested two types of fit statistics of RM to describe how well the data encounter the requirements of the model, e.g. outfit and infit statistics. The outfit statistic (outlier-sensitive fit) is an average of the standardized residuals and more sensitive to unexpected remarks by users on QOS attributes, which are relatively very easy or very hard for them. The infit statistic (Inlier-pattern-sensitive fit statistic) is a weighted standardized residual, which gives an idea about the unexpected behaviour affecting QOS attribute's rating near the user's ability level.

For attribute fit, an unweighted fit mean-square (outfit) is derived as:

$$MNSQ_{outfit} = \frac{\sum_n Z_{ni}^2}{N} = \frac{1}{N} \cdot \sum_n \frac{\left(X_{ni} - E\left(X_{ni}\right)\right)^2}{\mathrm{var}\left(X_{ni}\right)}, \quad (11)$$

the weighted fit mean-square (infit) is derived as:

$$MNSQ_{infit} = \frac{\sum_n Z_{ni}^2 \cdot \text{var}\left(X_{ni}\right)}{\sum_n \text{var}\left(X_{ni}\right)} = \frac{\sum_n \left(X_{ni} - E\left(X_{ni}\right)\right)^2}{\sum_n \text{var}\left(X_{ni}\right)}, \quad (12)$$

where: N – total number of auto-users participated.

2.5. Clustering the ranges of AUS$_i$ scores

Defining ALOS criteria is basically a classification problem. Each users' (drivers) may perceive the same object from widely varying sensory inputs, which is not restricted to a single class. The crisp clustering techniques restrict an object to a single class. However, Fuzzy partition can cluster corresponding properties human perception in which overlapping is endorsed for the identification of genes that are conditionally co-regulated or co-expressed. Participants can be grouped into fuzzy clusters based on their needs, choices, and psycho-graphic profiles. Bezdek (1981) proposed a popular and efficient clustering technique i.e. FCM, which is different from other clustering algorithms. FCM does not assign a data to a particular group, rather assigns each data point with a membership function. This membership function depicts belongingness of a specific object with all the groups. One $n \times c$ matrix $U\left[\mu_{ik}\right]$ symbolizes the fuzzy partitions with its limiting conditions as shown in following Equations (13)–(15):

$$\mu_{ik} \in \left[0,1\right],\ 1 \le i \le n,\ 1 \le k \le c; \quad (13)$$

$$\sum_{k=1}^{c} \mu_{ik} = 1,\ ; 1 \le i \le n; \quad (14)$$

$$0 < \sum_{i=1}^{N} \mu_{ik} < n,\ 1 \le k \le c. \quad (15)$$

Dunn (1973) proposed that the FCM clustering algorithm is established on the minimization of an objective function called c-means functional, which is derived as:

$$J\left(X; U, V\right) = \sum_{i=1}^{c} \sum_{k=1}^{n} \left(\mu_{ik}\right)^m \cdot \left\| X_k - V_i \right\|_A^2, \quad (16)$$

where: $V = \left[V_1, V_2, V_3, ..., V_C\right]$, $V_i \in R^n$ indicates a vector of cluster centres; X represents the data set; U denotes the partition matrix; V_i represents the mean of data points over cluster i; m denotes the weight exponent, which determines the fuzziness of the clusters; n indicates the number of observations; c indicates the number of clusters.

3. Selection of study area

An essential criterion in selecting the study area was to incorporate a varied range of road conditions to determine satisfaction level of drivers. Any random variable cannot be taken arbitrarily for the analysis, e.g. If the provision of separate bus pull-out lanes will be chosen as an influential factor, then its reliability index was required to be checked, whether drivers' are responsive to it or not. In the similar way, many QOS attributes are found to be subjective, but a small number of them are dealing with both perception and psychology of automobile users. Therefore, a pilot survey has been carried out first and it is followed by statistical calibration through factor analysis and Rasch analysis.

To identify the diverse set of issues affecting auto-driver's perception, the required perception data sets were collected from thirty-four urban street segments of three mid-sized Indian cities, namely Rourkela, Bhubaneswar and Vishakhapatnam as shown in Figure 2a. The basis for selecting the above three cities was to incorporate different types of urbanised areas, influencing drivers' expectations and experience of roadway conditions under mixed traffic stream. Rourkela is popularly known as the steel city of Odisha state. The selected road segments of this city carries urban residential setting with less traffic volume, which are separated from commercial zones. Almost each studied segments in this city have two lanes in each direction with a raised grassy median and sidewalk facility along with the road. Hence, landscaping become more apparent for these segments with clean and smooth road surface quality. Most of the drivers prefer private cars as their primary mode of transportation. Bhubaneswar, the capital of Odisha state is a city with primarily medium-density commercial development. At some points, the road width narrow downs due to on-street commercial activities. There are authorised or unauthorised on-street parking at several locations along with the roadway. The roadway cross-section begins with one lane and expanded to four lanes at various points. Some road segments are having medians and short stretches of sidewalk along with the lanes, whereas, some segments do not have these facilities. Self-regulating three-wheelers, taxis, two wheelers and local buses are the main modes of transportation in this city. Vishakhapatnam is one of the largest city in Andhra Pradesh and located around busy commercial areas near the financial district. At some places, dense commercial developments are closed to roadway and some street segments continued to an urban area with light to medium-density commercial developments. The routes are passing through residential areas and connected to high-density streets. The effect of transit mode is very high, for which pedestrian traffic was very high along many portions of the road stretch. Some portions of the lanes also contain separate bus pull-out lanes. Cycling is also an important mode choice to support public transport and to perform short trips. The average speed of vehicles varies from 15 to 50 km/h, according to the level of congestion to which the drivers are exposed.

The objective of this research is to include contextual diversity in the sample data sets, so as to observe as many differences as possible in drivers' behaviour. Hence, the above three cities were selected for exposure of partici-

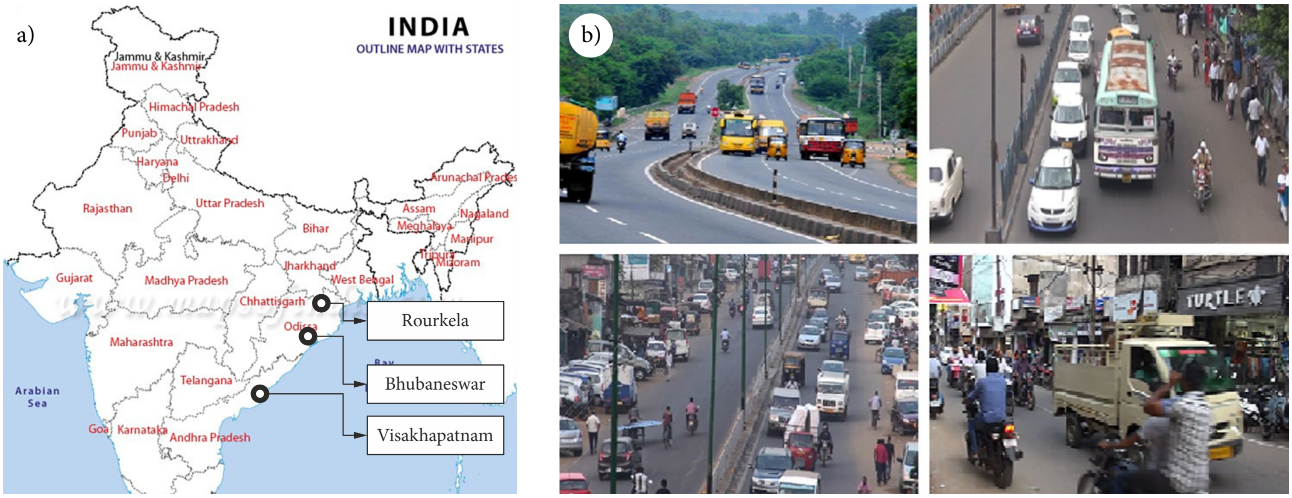

Figure 2. Map showing three cities across India selected for perception survey (a) and snapshots of several study locations ranging from best to worst provided service qualities (b)

pants to a variety of driving environment to identify diverse set of issues related to service quality. The behaviour and composition of traffic along with the road infrastructures are different from each other in the above three cities. Hence, these data sets can well represent the heterogeneity and complexity of provided transportation service. The samples of three road segments showing the variation in offered service quality are represented in the Figure 2b.

4. Data collection

The major objective of this study is to assess the satisfaction level perceived by auto-users while driving on the street segment. Ignoring travel behaviour, any strategy suggested by the transportation policy would be objectionable to the community when it will be implemented. Therefore, users' perception survey was conducted to judge real-time response of drivers. Roughly, nine hundred seventy-seven automobile drivers had taken part in travellers' intercept survey, in which drivers' responses have been recorded immediately after driving the street segment. This survey is a cost effective method to collect relatively large sample size and to represent a wider driving population. The perception survey has been conducted with the help of an innovative questionnaire, which is subdivided in to two phases. In phase 1, demographic information of the automobile users has been collected; and in phase 2 drivers were asked to rate each QOS attributes based on their perceptible potential under mixed traffic flow conditions.

4.1. Phase 1: collection of demographic variables

The perceived satisfaction level of an individual while using any facility differs from one person to another. Hence, driver's personal profile (like gender, age, driving experience and type of vehicle) were added to the questionnaire in phase 1, to incorporate diversity of human perception. The collected demographic information of different types of drivers are listed in Table 2.

Table 2. Demographic characteristics of survey participants

Attribute	Distribution	Frequency	Percentage [%]
Gender	Female	410	42
	Male	567	58
Age	18…25 years (young age)	371	38
	26…40 years (middle age)	352	36
	>40 years (old age)	254	26
Type of vehicle user	Motor bikes/ two-wheelers	410	42
	Cars	391	40
	LCVs	176	18
Driving experience	<5 years	186	19
	5…15 years	469	48
	>15 years	322	33
Total participants		977	100

4.2. Phase 2: perception survey on various QOS attributes

A number of QOS attributes, those may affect the auto-user's satisfaction level while driving on the road were included in phase 2 of the survey questionnaire. After a thorough understanding about the role of each variable affecting driver's comfort level, the whole questionnaire was made by producing 23 QOS attributes grouped together under six major dimensions. The attributes were articulated in a Likert scale ranging from 1 (highly dissatisfied) to 5 (highly satisfied) to get exact responses of auto-users for each attribute. Drivers were given the survey questionnaire to rate the attributes according to their conception or some of them were orally questioned about the attribute's quality on the study site itself. For each dimension, there is also an OS score in the similar way. The six major dimensions and their controlling QOS parameters are described below:

1) Roadway design:
   - number of lanes and lane width;
   - U-turn capacity;
   - provision of separate bicycle lanes;
   - bus pull-out lanes;
2) Traffic facilities:
   - on-street parking facilities;
   - number of stops or coordinated signal;
   - grade separation or more number of bypasses;
   - lane guidance signs/channelization;
3) Traffic operation:
   - travel time and delay;
   - speed limit;
   - cycle length at intersection;
   - Visual sign clutter and overhead flashing signs;
4) Pavement management:
   - riding quality and smoothness (cracking, rutting, surface skidding, etc.);
   - cross slope of carriageway;
   - visibility of road signs and markings;
5) Safety and comfort:
   - side friction (roadside commercial activities);
   - slope of speed breakers;
   - flat/steeper slopes at horizontal and vertical curves;
   - presence of median barrier;
6) Aesthetics:
   - cleanliness, road side ditches, pot holes;
   - amount of landscaping on roadsides and median with trees;
   - overgrown foliage on sidewalks;
   - proper street lightening at night.

The OS score for each segment was also inquired on the same five-point rating scale based on user's perceptible potential under the influence of mixed traffic flow condition.

5. ALOS model development

In this study, 75% of total responses were utilized for the development of ALOS model. Therefore, the collected response of 727 participants were fed and analysed with the help of WINSTEPS (*https://www.winsteps.com*) software. These responses belong to the 20 street segments, having varying road geometrical features and traffic flow conditions to provide different service levels for the drivers under mixed traffic condition. Perception data of 250 participants from remaining 14 segments were kept aside for model validation purpose. To examine the quality of fitting of the predicted model with overall data sets, the overall fit statistics and reliability of the proposed ALOS model are shown in Table 3. A reliability index of 0.86 and 0.96 was found out for the auto-users and QOS attributes respectively. The mean attribute difficulty was set to zero, and mean user's ability was set at −1.8 logit, which means that attribute content was considered to be slightly more difficult for the drivers.

5.1. Statistical significance of the input parameters

In order to examine the significance of selected variables in ALOS model, attribute's quality was displayed with the help of attribute measures in Table 4. All the attributes were sorted in increasing order of their quality or decreasing order of logit scale. The expectable range of outfit and infit mean-square should be within 0.6 to 1.4 according to Bond and Fox (2003). Standardized fit statistics Z_{std} express the statistical significance of the chi-square statistics. Oreja-Rodríguez and Yanes-Estévez (2007) mentioned that the data will be fitted to the model, while Z_{std} have an acceptable value between −3.0 and +3.0 standard deviations from the mean and outside of it indicate misfit at 95% confidence level. Higher the attributes' difficulty measure, more difficult that attribute was perceived by the users. The infit Z_{std} and outfit Z_{std} values of 18 attributes were found out to be reliable as their Z_{std} values fall within ±3.00 standard deviations from mean. Five attributes, namely amount of landscaping, grade separation, cycle length of intersection, slopes at curve corners and street lightening at night were dropped from the analysis as they were not significantly rated to validate. The most difficult situation, which creates dissatisfaction among the auto-users is the absence of separate bike lanes, bus pull-out lanes and parking facility. Simultaneously, road marking and slope of speed breakers are revealed as the low difficult attributes to deliver a comfortable drive. All the attributes

Table 3. Overall fit statistics and reliability of the proposed model

For auto-users		For QOS attributes	
727 input	727 measured	23 input	23 measured
Count	23	Count	727
Mean ability measure	−1.8	Mean difficulty measure	0.0
RMSE	0.67	RMSE	0.10
Infit mean-square	0.96	Infit mean-square	1.0
Infit Z_{std}	−0.1	Infit Z_{std}	−0.4
Outfit mean-square	0.97	Outfit mean-square	0.97
Outfit Z_{std}	−0.1	Outfit Z_{std}	−0.7
Reliability	0.86	Reliability	0.96

Table 4. Attributes' measure order: ranking of QOS attributes according to difficulty level

QOS attributes	Raw score	Difficulty measure	Standard error	Infit		Outfit	
				MNSQ	Z_{std}	MNSQ	Z_{std}
Amount of landscaping	248	3.16	0.18	1.18	0.8	2.12	3.3
Bus pull-out lanes	541	0.91	0.06	1.09	1.0	1.03	0.4
Bike lanes	663	0.52	0.06	0.95	−0.6	1.01	0.1
On street parking	679	0.47	0.06	0.91	−1.1	0.91	−1.0
Grade separation	796	0.11	0.06	0.76	−3.0	0.74	−3.1
Side friction	819	0.04	0.06	0.90	−1.2	0.86	−1.5
Delay	822	0.03	0.06	1.24	2.6	1.17	1.8
Cycle length at intersection	851	−0.06	0.06	0.74	−3.3	0.74	−3.2
Cleanliness	853	−0.07	0.06	0.89	−1.2	0.86	−1.6
No. of lanes/lane width	867	−0.11	0.06	1.17	1.9	1.10	1.1
Slopes at curve corners	872	−0.13	0.06	0.73	−3.3	0.74	−3.1
U-turn capacity	888	−0.18	0.06	0.81	−2.2	0.79	−2.4
Speed limit	890	−0.19	0.06	0.88	−1.3	0.88	−1.3
No of stops or coordinated signal	890	−0.19	0.06	0.90	−1.2	0.85	−1.7
Lane guidance/channelization	895	−0.21	0.06	1.30	3.0	1.22	2.3
Riding quality and smoothness	913	−0.27	0.06	0.92	−0.9	0.89	−1.2
Street lightening at night	916	−0.28	0.06	1.87	7.6	2.01	8.4
Median barrier	923	−0.30	0.06	0.93	−0.7	0.93	−0.8
Visual sign clutter	941	−0.37	0.06	1.01	0.2	0.97	−0.2
Overgrown foliage	983	−0.53	0.06	0.73	−3.0	0.74	−2.9
Cross slope of carriageway	989	−0.55	0.06	0.78	−2.4	0.78	−2.4
Slope of speed breaker	992	−0.56	0.06	1.22	2.1	1.29	2.7
Signs and markings	1131	−1.23	0.08	1.26	2.2	1.40	3.0

shown in Table 4 were considered as unidimensional and the attributes' difficulty ranges from +3.16 to −1.23 logit. Thus, a spread of almost 4.39 units of attributes difficulty was noticed from the unidimensional model. Attributes' reliability primarily influenced by the variance in attributes' difficulty. If the range of difficulty is wide, it will show high attribute's reliability. Therefore, the measurement of satisfaction found out from above sets of QOS attributes appeared reliable. However, the wider range of difficulty indicates the existence of multidimensionality, which was explored again to increase the level of accuracy.

5.2. Dimensional model

To resolve the problem of multidimensionality, Rasch analysis was applied to each dimension. There are $K = 6$ dimensional variables formed by the users' coefficients θ_{ik} ($i = 1, 2, .., n$; $k = 1, 2, .., K$) and a ranking of QOS attributes for individual dimension. Thus, the QOS attributes seem correctly directed to the auto-user's satisfaction. This can be considered as a symbol of a higher level of accuracy. The correlation coefficients for each dimension was found out with the help of factor analysis and the weight coefficients were calculated using Equation (7). The first eigenvalue of the correlation matrix was found out to be $\lambda = 3.86$. The correlation matrix resulting from factor analysis between 6 measures of different dimensions and their respective weight coefficients are shown in the Table 5. Individual AUS_i score was calculated from the linear combination of θ_k and their respective weight coefficients w_k for each dimension, which was presented in Table 6.

5.3. Ranges of service categories (A–F) defined by using FCM clustering

The estimated values of AUS_i for each participant were clustered into six numbers of ALOS categories with the help of FCM clustering technique. The threshold values of predicted AUS_i scores assigned to six ALOS categories (A–F) are shown in Figure 3. Finally, the predicted AUS_i scores for each urban street segments were calculated and the corresponding ALOS categories are charted in Table 7.

6. Model validation

The developed ALOS model was validated using data sets of fourteen randomly selected segments. Performance of ALOS model was compared with the collected 250 auto-users' perception data from fourteen street segments. Predicted AUS_i scores were calculated using the proposed model and classified into six ALOS categories with the help of FCM clustering technique. The perceived

Table 5. Correlation matrix and weight coefficients of six dimensions from factor analysis

	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
Column 1	1	0.7529	0.5828	0.6838	0.5626	0.612
Column 2	0.7529	1	0.6012	0.6205	0.5911	0.550
Column 3	0.5828	0.6012	1	0.4139	0.5897	0.400
Column 4	0.6838	0.6205	0.4139	1	0.4452	0.577
Column 5	0.5626	0.5911	0.5897	0.4452	1	0.473
Column 6	0.612	0.550	0.400	0.577	0.473	1
Factor analysis: (where, the first eigenvalue $\lambda = 3.86$)						
Measures	First factor f_1	Correlation coefficient ρ_{f_1,θ_k}	Weight w_k			
Measure 1	0.924	0.999	0.259			
Measure 2	0.894	0.753	0.195			
Measure 3	0.708	0.583	0.151			
Measure 4	0.764	0.687	0.178			
Measure 5	0.727	0.564	0.146			
Measure 6	0.716	0.61	0.158			

Table 6. Values of θ_k for six dimensions and respective AUS_i values of each participant

User	Roadway design	Traffic facilities	Traffic operation	Pavement condition	Aesthetics	Safety and comfort	AUS_i
1	−0.41	0.48	1.12	0.73	−1.15	−1.41	−0.10491
2	−0.41	0.99	0.36	−0.71	1.83	−1.41	0.05776
3	−0.5	0.99	0.73	0	0.5	−1.14	0.06543
4	−0.31	0.48	1.12	−1.47	−0.03	−1.14	−0.26335
5	−0.31	0.99	2.09	0.73	−0.03	−0.9	0.40892
6	−0.12	0.99	0.73	0	0.5	−2.16	0.00269
7	−0.94	−0.23	2.09	0.73	−0.56	−2.16	−0.26808
8	−0.12	0.99	2.88	0	0.5	−1.73	0.39313
…	…	…	…	…	…	…	…
477	0.21	0.72	0.36	0.73	2.92	1.42	1.02576

Table 7. Predicted AUS_i scores and respective ALOS categories for urban street segments

Street ID	AUS_i	ALOS category
1	1.77	B
2	2.55	A
3	1.727	B
4	0.35	C
5	−1.147	E
6	0.164	D
7	0.38	C
8	−2.01	F
9	1.64	B
10	2.26	A
11	1.53	B
12	2.24	A
13	0.719	C
14	−1.6	E
15	−0.33	D
16	1.35	B
17	−2.379	F
18	0.87	C
19	−0.75	D
20	1.1	B

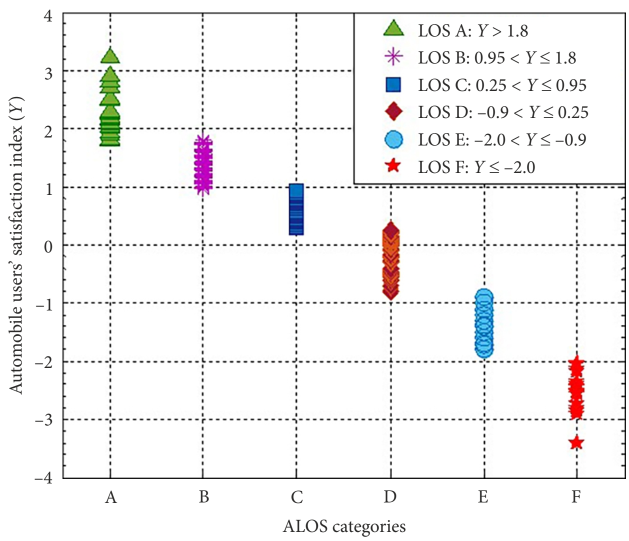

Figure 3. Clustering AUS_i scores to define the ranges of six ALOS categories (A–F)

user satisfaction scores for a particular road segment was calculated by taking the average of users' OS ratings for respective segments. The mean value of perceived ALOS scores obtained in this survey was almost 3, which corresponds to the boundary between ALOS category "C" and "D". From this boundary point, perceived OS scores were manually classified for six service categories as shown in Table 8.

The predicted vs perceived ALOS categories were compared with each other in Table 9, which shows that the model fulfilled a good validation with significance matching of ALOS categories.

Table 8. Ranges of OS scores for service categories (A–F)

ALOS	Service quality	Ranges of OS score
A	very good	OS score > 4.37
B	good	3.67 < OS score ≤ 4.37
C	average	3 < OS score ≤ 3.67
D	below average	2.33 < OS score ≤ 3
E	poor	1.66 < OS score ≤ 2.3
F	very poor	OS score ≤ 1.66

Table 9. Comparison between predicted ALOS and perceived OS scores

Street ID	AUS_i	ALOS	Perceived OS
1	0.86	C	3.6 (C)
2	−0.27	D	2.8 (D)
3	0.37	C	3.2 (C)
4	2.26	A	4.4 (A)
5	0.51	C	3.5 (C)
6	0.49	C	3.3 (C)
7	−0.53	D	2.9 (D)
8	0.32	C	3.2 (C)
9	−1.13	E	2.1 (E)
10	1.29	B	4.1 (B)
11	1.77	B	4.11 (B)
12	0.59	C	3.58 (C)
13	0.97	B	3.8 (B)
14	−2.24	F	1.4 (F)

7. Differential item functioning (DIF)

It is a graphical representation that takes place while distinct groups of participants respond to a QOS attribute in different ways, e.g. while examining the satisfaction level of drivers of two-wheelers, cars, three-wheelers and LCVs for a particular road segment, each group of users had a distinct line of DIF measure. Linacre (2012) suggested that the more difficult an attribute is to endorse, the greater is the DIF measure. The plotted DIF measures shown in Figure 4. indicate which attributes are more dif-

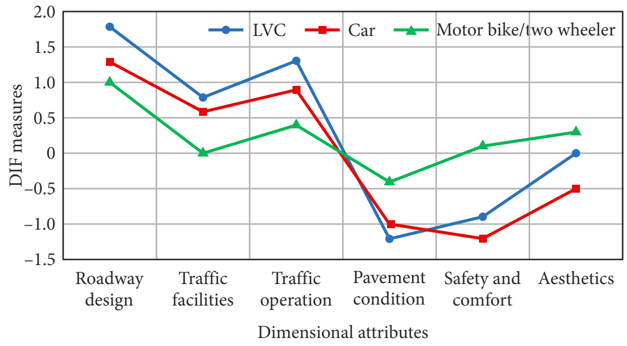

Figure 4. DIF measures for three groups of vehicles in automobile mode of transport

ficult to endorse for the auto-users within the compared groups. The six dimensional attributes are represented on the horizontal axis and DIF measures are on the vertical axis. The higher DIF measure of roadway design and traffic operation for LCV, indicates that roadway design attributes are somewhat more difficult to endorse for LCV users than other two modes. The same attributes are comparatively easier to endorse for cars and very easier for two-wheelers under mixed traffic flow conditions. This indicates that, the lane width is sufficient for two-wheelers to freely enter into mainstream and taking U-turn. Whereas, the LCVs experience more delay in through movement due to frequent stopping of public transits and interacting with non-motorised vehicles than the private cars. LCVs are unable to take U-turn easily due to insufficient width of turning lane at some segments. For traffic facilities, the LCV users and cars have reported to find insufficient space to park their vehicles, while, two-wheelers can easily avail the parking facility due to the requirement of lesser dimensional space. Similarly, for traffic operations, the LCVs and cars experience more delay in driving (at a speed lower than their speed limit) due to the interaction with heavy vehicles, non-motorised vehicles and on-street pedestrians. Whereas, two-wheelers generally experience less delay due to their freedom to manoeuvre. Poor quality of pavement structure undermines the smooth riding of two-wheelers, while, cars and LCVs are comparatively less affected by the bouncing of vehicles due to the poor pavement surface quality. DIF measure of safety and comfort level for two-wheelers increases in the absence of median barrier and steeper slopes at horizontal curve corners. Hence, it draws the conclusion that two-wheeler users are more susceptible to injury than the LCVs and private car users in presence of protective shields around them. Likewise, motor bikes are mainly affected by road side ditches, pot holes and over grown foliage of the sidewalks etc. as they often share the carriageway nearer to the sidewalks. However, LCVs and cars are comparatively less affected by the same attributes, which can be clearly found out from the lesser DIF measures of "aesthetics" for LCVs and private cars.

Summary and conclusions

The mixed traffic flow characteristic in developing countries like India is significantly different from homogeneous traffic conditions. Therefore, the existing approaches can be justified by considering the complexity of the service quality concept and identifying the actual need of drivers. RM is distinctive from others as it identifies a set of quantitative measures those are free from any subjective as well as objective traits. Hence, it was easy to evidently categorize the attributes those are more difficult to produce satisfaction and to identify the variation in response of different modes of transport. This study also assists the investigation of motivations and barriers to different modes of transport through DIF plot.

The results presented in Table 7 indicates that 15% of the road segments (e.g. street ID 2, 10 and 12) are subsiding under ALOS category A, which have delivered proper facilities to the users for a safe and comfortable drive. Similarly, 30 and 20% of the road segments are designated with ALOS B and C respectively. Based on the discussions with few auto-drivers/stakeholders, it was acknowledged that the slight dissatisfaction is mainly due to the interruption by public transit ahead while driving on the road (street ID 1, 3, 9, 11, 16 and 20). Along with that the improper parking facilities and amount of landscaping significantly decrease the auto-users in the above segments (street ID 4, 7, 13 and 18). 15 and 10% of the segments are assigned to ALOS D and E respectively, which is mainly due to the roadside commercial activities, insufficient U-turn capacity etc. on street ID 6, 15 and 19. Furthermore, sufficient lane width, rough roads and cleanliness have an adverse effect on the satisfaction level of drivers on street ID 5 and 14. Correspondingly the worst road condition (ALOS F) encountered by the drivers is on street ID 8 and 17. These street segments neither provide sufficient lane with, median barrier, proper street lightening nor the above-discussed factors. These field observations are indicative in nature to draw the conclusion.

This qualitative study has identified a set of quantitative measures from the pilot survey and integrated them in a structured manner to help in determining auto-user's satisfaction level under the prevailing road and traffic conditions. Some key factors, influencing the satisfaction level of auto-users both positively and negatively, are also highlighted with the help of attribute measure table. Some service attributes, such as: absence of separate bike/bus pull-out lanes, improper on-street parking facility and roadside commercial activities have considerable negative impacts on the perceived comfort level of drivers. While, some other attributes, like road signs and markings, slope of speed breaker and cross slope of carriageway have considerable positive impacts on the users' satisfaction. These factors are very common for highly mixed traffic flow characteristic of Indian cities; although significantly different from homogenous traffic conditions. It is observed from this study, the complexity of the service quality concept and identifying the actual need of drivers in Indian urban clusters are of similar nature although they are geographically separated from one to other. Considering the diversity of human population in development of ALOS model, it is anticipated that these study findings will be well applicable to forecast the service quality of urban street segments in other Indian cities and to boost users'-friendly environment in developing countries.

These assessments will be helpful for the planners and decision makers in number of ways. First of all, the attribute measure order would be a useful technique to implement several design alternatives by identifying specific road attribute, which should be mainly prioritized to enhance the operational efficiency of road infrastructure. The ALOS scores can help the transportation planners to recognize the extent of need for further developments of existing roads. Accordingly, the budgets for improvements can be optimized to achieve desired performance of the road infrastructures and weak links in the road network requiring upgradation will be prioritized based upon its index values.

As observed in this study, the urban roadways are generally shared by motorized two-wheelers, three-wheelers, cars, buses, non-motorized vehicles and pedestrians, etc. without any lane discipline, which often leads to uncontrolled traffic operation, lower travel speed and congestion during peak hours. The users' satisfaction score is also lower under such driving environment because of the prevailing conditions. However, traffic characteristics are somewhat different for developed countries and users' perceived satisfaction scores may vary accordingly. This model can perform well, when all the input variables and output variable (AUS_i scores) are within the range of operating conditions related to the present context. Therefore, the proposed model has got scope of wide application in mixed traffic conditions, whereas, it needs further investigations related to the service attributes, affecting comfort level of drivers in homogenous traffic flow conditions. To overcome this limitation, the methodology needs some modifications by iteratively changing the input parameters in varying road and traffic conditions for effective assessment of the service quality of urban street infrastructures in a global scenario.

This study provides guidelines to evaluate existing roadways and to determine current ALOS on different road segments. On the other hand, growth of traffic might be a main consideration in future investigations because of exponential increase in the demand of automobiles. This congestion in the traffic stream will be expected to rise due to space constraint that limits widening of roads. Accordingly, the driving experiences and expectancies across different locations will change. The authors suggested that the most important factors found to influence users' perceptions of service quality should be controlled in future experiments to achieve the desired road performance. Hence, this study methodology can be feasibly applied by the transportation planners while assessing performance of a road infrastructure in future, by changing the independent variables in accordance with the drivers' expectations.

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