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Interrelationships among service quality factors of Metro Rail Transit System: An integrated Bayesian networks and PLS-SEM approach

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ABSTRACT

Finding ways to improve the service quality and consequently attract more passengers is a major concern for public transit officials worldwide. Given the fact that there is a glaring deficiency of service quality models in the literature, especially for developing nations, the present study develops interrelationships among service quality factors of Metro Rail Transit System (MRTS) in Delhi, India. For this purpose, the study implemented an integrated Bayesian Networks (BN) and Partial Least Squares Structural Equation Modelling (PLS-SEM) approach on perceptions of 2390 passengers of Delhi Metro. Firstly, the study extracted 41 service quality indicators into eight service quality factors using principal component analysis. Secondly, the extracted factors were learnt in BN to achieve the most robust network structure. Thirdly, the robust BN structure was tested and analysed in PLS-SEM to develop a service quality model. The integrated methodological approach has facilitated in identifying hidden interrelationships among service quality factors through a systematic manner. The developed model indicates 'passenger ease' as the most influential and 'amenities' as the least influential factors of overall service quality (OSQ). The OSQ index of 79.59 reveals the moderate satisfaction of passengers with Delhi Metro services. The study proposed several insights into the service quality improvements for Delhi Metro that must be focused and enriched for increasing Metro transit ridership. This knowledge of interrelationships among service quality factors can help transit officials in formulating effective strategies and investment plans accordingly to meet the passengers' needs.

1. Introduction

The study on service quality has become an essential and critical issue for the improvement of public transit systems. Enhancing service quality and understanding the relationships among its factors provide transit providers and government authorities, a way to retain the existing passengers and entice new ones (Díez-Mesa et al., 2018; Kim et al., 2018). The interrelationships among service quality factors of public transit greatly vary across the context (developed or developing nation), and transit system (Metro Rail, Light Rail, or Bus Transit). This is due to the disparity in service availability, lifestyles, individual characteristics, journey type, etc. of transit passengers (Das and Pandit, 2016). With the huge investments in rapid transit systems in recent years (NTDPC, 2014), studies on service quality are very much essential to rapidly developing cities like Delhi, India, than never before. Such studies will help

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public transit officials to focus on the areas which need improvement or have significant importance to the passengers and plan the strategies accordingly to meet the passengers' needs (De Oña and De Oña, 2014; Liou et al., 2014).

Over the two decades, studies on service quality of public transit systems based on passengers' perspective have gained significant attention from the researchers worldwide (Awasthi et al., 2011; Aydin, 2017; Nathanail, 2008). These studies indicate that addressing passengers' level of satisfaction towards public transit usage can tackle many urban mobility issues like private motorization, traffic congestion, pollution, etc. For instance, Li et al. (2018) reveal that an increase in passenger satisfaction is susceptible to frequent usage of public transit. However, poor transit service quality is attributable to private mode shift, thereby increasing traffic congestion (Deb and Ahmed, 2018; Singh, 2012). Therefore, passengers' perspective acts as an important element in improving the ability of public transit to compete with the other modes of transportation (De Oña et al., 2013; Machado-León et al., 2017).

Service quality is a combination of several indicators/attributes (observed variables) such as service frequency (Cheng and Chen, 2015; Tyrinopoulos and Antoniou, 2008), network coverage (Joewono and Santoso, 2015; van Lierop and El-Geneidy, 2016), transfer facilities (Isikli et al., 2017; Machado-León et al., 2017), waiting time (Awasthi et al., 2011; Grujičić et al., 2014), level of comfort (De Oña et al., 2016a; Machado et al., 2018), etc., grouped into factors (unobserved variables) such as service availability (BS EN 13816, 2002; Díez-Mesa et al., 2018), accessibility (Allen et al., 2020; De Oña et al., 2013), reliability (Eboli and Mazzulla, 2009; Liou et al., 2014), comfort (BS EN 13816, 2002; Eboli and Mazzulla, 2015), etc. These factors are important aspects in the study of overall service quality (OSQ) (Parasuraman et al., 1985); however, complex, ambiguous, and fuzzy interrelationships exist between them in different ways (Díez-Mesa et al., 2018).

Existing studies show traces of the direct and indirect impact of service quality factors on OSQ or passenger satisfaction (De Oña et al., 2018; Díez-Mesa et al., 2018; Eboli and Mazzulla, 2012; Liou et al., 2014; Rahman et al., 2016). For instance, Liou et al. (2014) highlighted that the OSQ of bus transit in Taipei city relies on factors such as driver's attitude, equipment, convenience, and reliability. It was revealed that the indicators of 'equipment' factor affect service quality satisfaction directly as well as indirectly via indicators of 'driver's attitude' and 'reliability' factors. The study of De Oña et al. (2018) found that 'comfort and convenience' factor influences 'transport service' factor and has an indirect effect on users' satisfaction through 'transport service' factor. However, these interrelationships between service quality factors need to be explored through a systematic approach that replicates the real-world.

So far, researchers employed different approaches such as Decision Tree (De Oña et al., 2015), Multinomial Logit (MNL) model (Eboli and Mazzulla, 2008; Hensher et al., 2003), Structural Equation Modelling (SEM) (Deb and Ahmed, 2018; Lai and Chen, 2011; Li et al., 2018), Importance-Performance Analysis (IPA) (Grujičić et al., 2014; Weinstein, 2000), Index Number approach (De Oña et al., 2016b), Rasch Analysis (Kim et al., 2018), Cluster Analysis technique (Abenoza et al., 2017; De Oña et al., 2014), and integrated approaches such as SEM-Multiple Indicator Multiple Cause (MIMIC) approach (Allen et al., 2020), and Bayesian Networks (BN) – SEM approach (Díez-Mesa et al., 2018), etc. in the service quality literature. Among them, most studies have employed SEM as a powerful and fundamental tool in exploring the interrelationships among various factors (Chou and Kim, 2009; De Oña et al., 2013; Zhang et al., 2019, etc.). SEM examines the relationships among the latent (unobserved) variables that describe as a linear combination of observed variables (Chen, 2008; Golob, 2003).

Literature suggests two distinct methods of SEM. Firstly and commonly used, Covariance-based SEM (CB-SEM) that estimates the relationships by minimizing the difference between theoretical and estimated covariance matrices (Golob, 2003). Secondly and less explored, Partial Least Squares-SEM (PLS-SEM) that determines the relationships by maximizing the explained variance of the endogenous latent variables (Henseler et al., 2016). PLS-SEM and CB-SEM have distinct characteristics. The selection of either of methods for examining interrelationships depends upon different criteria, mainly the nature of the study, data type, and subsequent analyses (Hair et al., 2011; Hair et al., 2017; Wu, 2010).

When the objective of the research is prediction and theory development instead of theory testing and confirmation, then PLS-SEM is the most preferred approach. More specifically, PLS-SEM is best suited for examining exploratory models (Hair et al., 2017). Unlike CB-SEM, PLS-SEM requires no assumptions of homogeneity and normality in the data, and hence, replicating real-world data (Hair et al., 2014). PLS-SEM efficiently deals with the issues of small sample sizes, latent variables with fewer items (i.e., one or two) and multicollinearity. In addition, PLS-SEM provides latent variable scores in a deterministic manner (Fornell and Bookstein, 1982). These scores can be useful for subsequent analyses. It attributes to the application of PLS-SEM approach in the customer satisfaction analysis for developing the American Customer Satisfaction Index (ACSI) and European Customer Satisfaction Index (ECSI) (Wu, 2010). Therefore, PLS-SEM stands as an attractive substitute to CB-SEM, in investigating the relationships in real-world scenarios.

The present study improves upon the shortcomings of using CB-SEM approach in reflecting the real-world scenario by employing PLS-SEM that addresses the passengers' perception data more efficiently, requiring no assumptions of homogeneity and normality in the data. Since, the interrelationships between service quality factors lack a previous theory, guessing causal directions between the factors becomes complicated and time-consuming in PLS-SEM analysis. Therefore, the present study contributes to the literature by suggesting an integrated methodological approach, i.e., Bayesian Networks (BN) and PLS-SEM to establish the interrelationships among service quality factors of the Metro Rail Transit System (MRTS) in Delhi, India. This integrated approach has been successfully employed by the researchers in the field of business management (Wu, 2010) and mathematics (Ouazza et al., 2018), yet unexplored in the transit service quality arena. The methodology consists of two following stages: firstly, to apply BN for building an exploratory model (network) from the available data; secondly, to test and analyse the built network using PLS-SEM for developing a service quality interrelationship model.

Both methods complement each other with their inbuilt specialties. BN is a data mining method, used to explore and learn the interrelationships from the available dataset, owing to the absence of theory grounding (Heckerman, 1996; Lauría and Duchessi, 2007). This way, BN tackles the limitation of PLS-SEM, i.e., needing prior knowledge of interrelationships to build an exploratory model. PLS-SEM approach is a causal-predictive technique that tests and analyses the exploratory model from the predictive perspective and helps researchers in theory development (Hair et al., 2014; Hair et al., 2019; Usakli and Kucukergin, 2018). Consequently, PLS-SEM assists in testing and predicting the relationships of the service quality model learnt from the BN. Hence, the suggested methodology is suitable for examining service quality interrelationships in the public transit sector.

More specifically, the present study makes the following contributions to transit service quality literature. First, the study employs an integrated BN and PLS-SEM methodology for establishing the theory of interrelationships among service quality factors of MRTS. Although Díez-Mesa et al. (2018) suggested a two-step methodology (BN with CB-SEM) for service quality models, the use of BN with PLS-SEM (a more robust approach) is the area of innovation in the transit service quality literature, contributed by this study. Second, the study enriches the concept of service quality from previous studies by developing context-specific interrelationships, specifically from developing nations context, i.e., Delhi, India. Literature also highlights the need to develop context-specific service quality models for public transit systems (Dagger et al., 2007; Díez-Mesa et al., 2018). Third, the present study uses an extensive, comprehensive, and rigorous dataset of 2390 passengers of the MRTS from Delhi, India. To the best of our knowledge, this study is first of its kind to have the experience of analysing a more complex, ambiguous, and uncertain perception data of an MRTS from a different geographical context (India) than expected in the existing literature. Such representative data is very much important for any MRTS to understand the true intentions of passengers in using the transit service again. Thus, the data we use is one of our contributions. Finally, the study examines the performance indices of service quality factors through latent variable scores. This index acts as a prescription tool for transit officials in formulating effective strategies for the improvement of transit service and comparing with other transit systems in India and worldwide.

This paper is ordered as follows. The subsequent section briefly describes the methodological approach. The third section demonstrates the study context and survey database. The fourth section illustrates the procedure for model development. The fifth section represents the study results. Sixth section discusses the inferences drawn from the study results. The final section deals with the conclusion and policy implications.

2. Methodological approach

The present study employs an integrated methodological approach involving BN and PLS-SEM for developing a service quality model. The following sub-sections explain the methodological approach in detail.

2.1. Bayesian Networks (BN)

Bayesian Networks (BN), also termed as ‘Belief Networks’, hails from the family of probabilistic graphical models. This graphical model approach is particularly famous for representing uncertain knowledge from the available data (Pearl, 1988). BN makes use of principles of different theories, i.e., probability theory, graph theory, and data mining theory, all together to investigate the interrelationships between the variables (Salini and Kenett, 2009). Hence, BN has the ability to make complicated problem analysis understandable by representing uncertain interrelationships (Hanninen, 2008).

The BN model is usually expressed in two parts. First is the quantitative part of the model, where the joint probability distribution (JPD) is computed by factorizing a set of conditional probability distributions. It is represented further in the form of Directed Acyclic Graph (DAG) structure.

Let $V = (X_1,\dots, X_n)$, be a set of n number of variables. A BN over a set of variables ‘V’ is a network structure, which is a DAG over ‘V’ and a set of conditional probability tables corresponding to each node, shown in Eq. (1) as:

$$P(X_i) = P(X_i|\pi_i, X_i \in V) \tag{1}$$

Here, π_i is a set of parents of X_i.

Accordingly, BN calculates the JPD over ‘V’, shown in Eq. (2) as:

$$P(V) = \prod_{i=1}^{n} P(X_i|\pi_i) \tag{2}$$

The second part of the model is the qualitative part, which employs a graphical model structure, typically termed as DAG. This DAG allows a useful graphical illustration of computed JPDs over the set of variables (Salini and Kenett, 2009).

BN is a DAG structure comprised of a set of nodes and a set of directed links (Kjaerulff and Madsen, 2008). The node indicates any kind of variable, be it observed variable, unobserved (latent) variable, or a hypothesis, and represented by a circle. The link (also termed as edge or arc) represents the existence of direct dependence among the variables and is denoted by an arrow between the nodes. Particularly, the two nodes with no link between them represent independence between the variables. In BN terminology, the node from which an arc directs outwards is a ‘parent’ node, and the node with an arc directed towards is a ‘child’ node.

Learning the BN structure is the primary step in BN analysis and can be done by two methods. The first is the manual learning method. This method requires experts’ knowledge, skills, and creativity to learn the structure, which is a time-consuming job. The second one is the automatic learning method, which is a computer-intensive method. It implements several algorithms for learning the BN structure directly from the available data (Cugnata et al., 2016). The automatic learning method involves three main approaches: constraint-based, score-based, and hybrid approach. The constraint-based approach learns the BN structure by analysing the conditional independence constraints, which are determined by performing the conditional independence tests on the data. The score-based approach maximizes the goodness-of-fit scores for learning the BN structure, as these scores explain how well interdependencies in the network match the data. The hybrid approach merges the principles of the above two approaches to learn the structure.

This research employs the automatic learning method to learn the BN structure because the motive behind using the BN approach is to build an exploratory model from the available data. Also, it is possible to integrate prior knowledge with automatic learning to determine the relationship structure. This paper reflects Cugnata et al. (2016) methodology for implementing the BN approach and selecting the robust BN structure.

2.2. Partial Least Squares Structural Equation Modelling (PLS-SEM)

PLS-SEM, also known as PLS path modelling, is a non-parametric method in the SEM family. This method integrates principal component analysis with ordinary least squares regression for investigating the interrelationships among manifest (observed) variables (MVs) and latent (unobserved) variables (factors or constructs) (Mateos-Aparicio, 2011; Tenenhaus et al., 2005). Two components usually explain a PLS-SEM approach, i.e., the measurement model and the structural model. The measurement model, also termed as an outer model, exhibits the relationship of MVs with their respective constructs. Whereas the structural model, also known as an inner model, exhibits the interrelationships between the constructs, which can be endogenous (dependent) and exogenous (independent) variables, by determining the path coefficients.

The measurement model of PLS-SEM, based on measurement type (reflective or formative), is expressed by two equations (3) and (4) (Tenenhaus et al., 2005):

$$\text{For reflective measurement; } x_h = \pi_{h0} + \pi_h \xi + \varepsilon_h \tag{3}$$

$$\text{For formative measurement; } \xi = \sum_h w_h x_h + \delta \tag{4}$$

where, x_h is MV, which refers to attribute or indicator; π_h is the loading corresponding to MV; ξ is the latent variable to which the MVs (x_h) are related; ε_h is the error term associated with MV; w_h is the weight corresponding to MV; δ is the residual term.

The structural model of PLS-SEM is expressed in Eq. (5) as follows:

$$\xi_j = \beta_{j0} + \sum_i \beta_{ji}\xi_i + v_j \tag{5}$$

where ξ_j is j^{th} latent variable with 'i' number of latent variables; β is the regression coefficient term for latent variables; v_j is error term associated with ξ_j.

For structural model estimation, PLS-SEM consists of three different weighting schemes, i.e., centroid weighting, factor weighting, and path weighting scheme, to examine the path coefficients. Though slight differences occur in the path coefficients by applying each of the weighting schemes, the path weighting is recommended because of its inbuilt advantages (Hair et al., 2017). The path weighting scheme gives a higher coefficient of determination (R^2) values for endogenous latent variables and is usually appropriate for all types of PLS path estimations. Checking the level of significance of path coefficients is the primary assessment criterion for the structural model. Besides, a coefficient of determination (R^2) measure indicates explained variance in endogenous construct (Shmueli and Koppius, 2011), thus referred as model's explanatory power. An R^2 estimate lies in the range of 0 to 1, a value near to 1 explains greater explanatory power (Hair et al., 2019). A measure of predictive relevance (Q^2) is an additional evaluation criterion to explain model's predictive accuracy (Geisser, 1974). This measure represents the ability of the model to predict the indicators of each endogenous construct efficiently. A Q^2 value, greater than zero, indicates adequate predictive accuracy of the model.

Further, the fitness of the PLS-SEM model can be assessed by using fit parameters such as Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), Unweighted Least Squares Discrepancy (d_{ULS}), Geodesic Discrepancy (d_G) and Root Mean Squared residual (RMS_theta). The SRMR and NFI hail from approximate fit indices family, while d_{ULS} and d_G belong to exact fit indices family. The SRMR is the difference between the empirical correlation and model implied correlation matrices and is checked to avoid model misspecification. A value of SRMR less than 0.08 is considered a good fit (Henseler et al., 2014). The NFI is an incremental fit measure with an acceptable value of 0.9 or above for good model fit (Hair et al., 2011). The exact fit indices, i.e., d_{ULS} and d_G are two different ways to test the statistical inference of the discrepancy between the empirical correlation and model implied correlation matrices. For obtaining substantial model fit, the d_{ULS} and d_G should be so small that it could be attributed to sampling error, and thus should not exceed the 95% quantile of the bootstrapped discrepancies (HI_{95}) (Dijkstra and Henseler, 2015). The RMS_theta is the measure of degree to which the measurement model residuals correlate. An RMS_theta value less than 0.12 represents a well-fitted model (Henseler et al., 2014).

This study employs PLS-SEM due to the following significant reasons. Firstly, the passenger perception data is heterogeneous and non-normal. Secondly, the nature of this research is exploration and prediction of interrelationships among service quality factors. Thirdly, PLS-SEM does not limit the researcher to have at least three items in each construct to avoid model identification problem (Anderson and Gerbing, 1988). It eases the present study in representing the 'Overall Service Quality' (OSQ) construct with only two observed variables. Lastly, PLS-SEM provides the latent variable scores for each construct given that constructs are modelled as determinate (Fornell and Bookstein, 1982). These scores have been useful for measuring the performance indices of service quality factors in the study. Hence, the use of PLS-SEM for analysing the exploratory model (extracted from BN) is well justified.

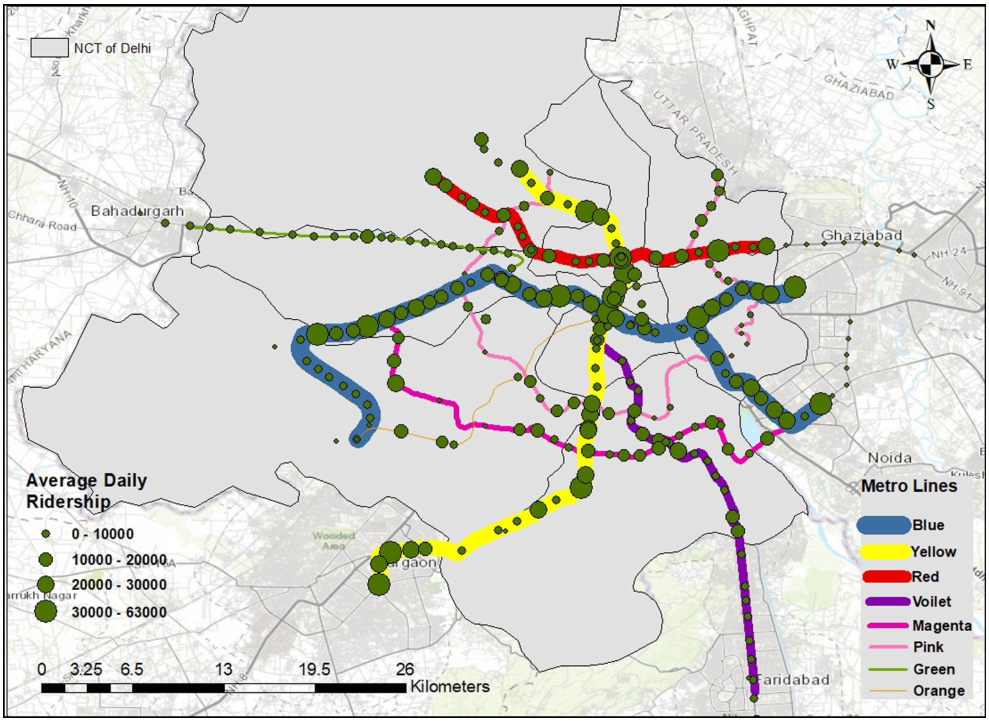


Fig. 1. Network coverage of Delhi Metro.

3. Study context and survey database

3.1. Study context

The capital city of India, Delhi, owns a well-established Metro Rail Transit System (MRTS). Since the year 2002, the MRTS is serving citizens of Delhi and its satellite cities. Within 15 years, the Delhi Metro stands 9th longest in network length, 16th highest in annual ridership, and 1st in earning carbon credits worldwide (DMRC, 2019). Currently, the Delhi Metro is operating with nine lines connecting 285 stations covering 391 km length. Fig. 1 shows the spatial distribution of existing Metro lines with their average daily ridership at transit stations. In the next ten years, the Metro corporation is adding 103 km of Metro network with an investment of ₹450 billion ($6.6 billion) (DMRC, 2019). However, demographic changes and economic growth in the last decade has contributed to a considerable decline in the Metro ridership (Ahmed et al., 2016). Recent reports indicate that the average daily ridership (2.56 million) is much lower than the expected ridership (4.5 million) that art needs to break-even (CSE, 2019). The situation of fast growth in private vehicles and the decline in transit ridership is worrying government agencies while looking at future investments. At this stage, improving service quality is an essential option to increase transit ridership. This study will be beneficial for transit providers to better understand the service quality aspects that require improvements or of significant importance. This eventually will increase transit ridership by retaining the current passengers and attracting the new ones.

3.2. Survey questionnaire

The present study conducts a passenger survey to capture their perceptions of the service quality of Delhi Metro. For this purpose, the study has developed a survey questionnaire with 45 service quality indicators based on the extensive review of service quality literature (BS EN 13816, 2002; De Oña et al., 2016a; Li et al., 2018; TRB, 1999). The questionnaire design has followed the principles of reliability, generosity, simplicity, and logicality. A pilot survey was conducted on 100 Metro passengers to ensure the simplicity and generosity of the survey questionnaire. Consequently, the questionnaire was revised to ensure the content validity with the following modifications: alteration in the sequence of questions, addition of new service quality indicators that relate to 'Ease of interchange', 'Interchange time', 'Mobile network connectivity', 'Women security', 'Access environment', and 'Air pollution' based on context and passengers' concerns, and removal of repeated or confusing questions. Also, the Cronbach's alpha value (0.87) has ensured the reliability of the survey questionnaire.

The final questionnaire is organized into three segments. The first segment collects information related to travel characteristics such as frequency of travel, trip purpose, journey time, trip origin and destination, access/egress distance, and access/egress travel mode. The second segment elicits passengers' perception of service quality. In this part, respondents perceive their level of satisfaction towards 41 service quality indicators on a 5-point Likert scale, 1 being 'highly dissatisfied' and 5 being 'highly satisfied'.

Table 1
Summary of sample size for each Metro line.

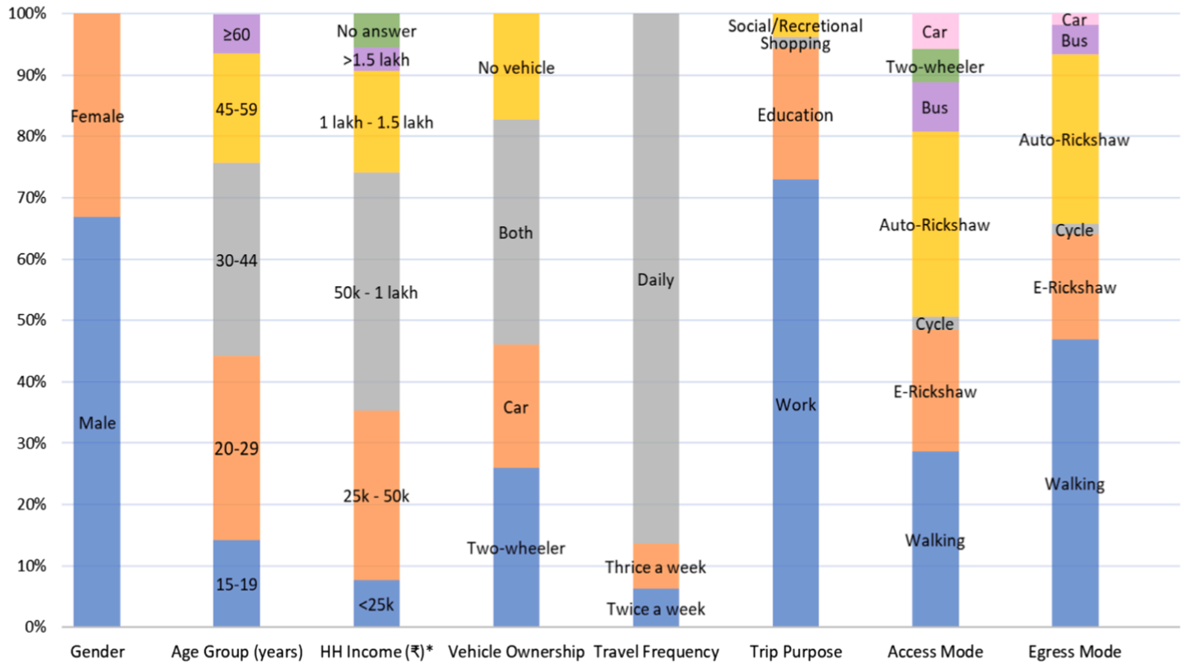
Line	Required Samples (Based on Krejcie and Morgan formula (1970))	Collected Samples	Complete Samples
Red	168	270	258
Yellow	451	460	455
Blue	488	500	491
Green	52	255	251
Violet	151	255	250
Pink	59	255	252
Magenta	102	255	249
Orange	31	50	43
Total	1502 (at 98% Confidence level and 3% error)	2390	2249

Also, the passengers express their perception towards ‘overall level of service’ and ‘overall level of satisfaction’ on the same scale. The final segment of the questionnaire incorporates questions related to the socio-economic characteristics of passengers, such as age, gender, qualification, occupation, household income, household size, and vehicle ownership.

3.3. Data collection

In this study, Tablet-based face-to-face interviews were carried out along nine Metro lines of Delhi from August 2019 to December 2019. This survey facilitates the passengers with the interviewer’s assistance to ensure good quality of data. The survey also ensures the issues of confidentiality by informing the respondents about the study motive and potential usage of data prior to their participation. The present study adopted stratified random sampling to reflect heterogeneity among passengers. During the survey, the interviewer approached the travellers on-board, at Metro station or platform. The frequency of travel in the Metro was the first question solicited to the respondents. The survey was continued further only if the respondent is a frequent traveller (twice a week or more). A total of 2390 responses were collected, covering all the nine Metro lines.

The present study considered 2249 cleaned and complete samples for subsequent analysis. Table 1 represents the summary of the sample size for each Metro line. On a scale of 5, passengers are highly satisfied (4.54) with ‘lighting of the Metro system (platform, terminal, and train)’ and least (3.55) with ‘mobile network inside Metro system’. The mean values of ‘overall level of service’ and ‘overall level of satisfaction’ are 4.08 and 3.87, respectively.



*$1 = ₹72.18 (As of March 2020)

Fig. 2. Socio-economic and travel characteristics of survey respondents.

3.4. Sample statistics

Fig. 2 depicts the detailed statistics on respondents' socio-economic and travel characteristics. The survey sample consists of 33% female and 67% male passengers, which attributes to nearly 30% female users of Delhi Metro (UITP, 2014). About 62% of passengers are between 20 and 45 years, whereas young (15–19 years), middle-aged (45–59 years), and elder (≥60 years) contribute to the remaining. Nearly 73% of passengers hold at least a graduate degree. It attributes to 72.9% of work trips in Delhi Metro. Interestingly, most (82.7%) passengers own at least one vehicle. However, their education qualification and self-motive may direct them to Metro usage. A higher proportion, i.e., 28.7% and 46.9% of passengers use walking as access and egress modes, respectively. The availability of personal vehicles drives them to Metro stations at the access ends, due to which walking at the egress side is higher. The most fascinating is, about 50.6% and 65.8% of Metro travellers are using sustainable transit modes, i.e., walking, cycling, and e-rickshaw to reach Metro stations and destinations, respectively. It is an interesting finding and accord previous studies that transit usage led individuals in sustainable transport choices (Kumar et al., 2020). It is worth highlighting that 86.4% of Metro users commute daily. Hence, the most frequent Metro users are adults (20–45 years), graduates, middle income (₹50 k − 1.5 lakh), and use sustainable modes.

3.5. Database preparation

This sub-section focuses on the preparation of the database to which the BN structure is to be learnt. It involves the determination of service quality factors (latent variables) by implementing a Principal Component Analysis (PCA) with Varimax rotation on the 41 perceived service quality indicators. Along with this, another PCA is executed on 'Overall level of service' and 'Overall level of satisfaction' variables to extract 'Overall Service Quality' (OSQ) factor. The indicators with a factor loading equal to or greater than 0.4 are retained and grouped under their related factors in PCA (Brons et al., 2009). This way, the service quality indicator 'M8′ and 'M33′ were removed due to lower (< 0.4) loadings.

The application of PCA extracted seven service quality factors and the OSQ factor according to 41 indicators. Table 2 represents the service quality indicators, and their related factors resulted from PCA. The eight extracted factors representing the service quality indicators of this research are as follows: Service Availability (SER_AVAIL), Passenger Ease (PASS_EASE), Passenger Information (PASS_INF), Amenities (AMEN), Safety and Security (SAFE_SEC), Seamless Connectivity (SEAM_CON), Environmental Impact (ENV_IMP) and Overall Service Quality (OSQ).

4. Model development

The procedure for implementing the proposed integrated methodological approach to develop the service quality model is described in the following two stages:

Stage 1: Building an exploratory model (network) from the available data

The BN algorithm learns the probable relationships among seven service quality factors and OSQ. The present study used *bnlearn* package in R software for extracting the most robust BN structure from the available data (Scutari, 2010). Based on the researchers' criteria and nature of the data, this study employed 16 algorithms (5 constraint-based, 8 score-based, and 3 hybrid learning algorithms) to learn different BN structures. The algorithms considered in this study are found to be sufficient to learn the most robust network.

For each of the learnt BN structures, the occurrence of an arc among two nodes is observed and scored as per the procedure elucidated in Cugnata et al. (2016). Then, the total score (also termed as arc strength) for each arc corresponding to all the learnt BN structures is determined. The most robust BN structure has the maximum arcs with an arc strength equal to or more than the threshold value of 11. The study established a threshold value of 11 as two-third of the total number of learnt BN structures. During the analysis, if there exists two robust BN structures with the same number of arcs having high arc strengths, BN structure with the minimum misclassification rate among the two is chosen.

Lastly, to examine the robustness of the chosen BN structure, bootstrap resampling process is executed on the original data. In this process, 1000 BN structures are learnt by implementing the same learning algorithm (which attained the most robust BN structure) on 1000 randomly generated subsets, each with 1000 random observations. This procedure obtains the occurrence proportion of arcs that indicate the robustness of the extracted interrelationships.

Stage 2: Testing and analysis of interrelationships

In this stage, the exploratory model extracted from BN is tested and analysed by PLS-SEM approach in *SmartPLS* software. The PLS-SEM algorithm applies the ordinary least squares regression in an iterative process to measure the partial path coefficients and latent variable scores (Hair et al., 2011). These latent variable scores are used for estimating the outer loadings of MVs.

The study assessed measurement and structural models separately. The measurement model, which represents the relationships of MVs with their respective constructs, is assessed for reliability and validity checks as per Hair et al. (2019). The structural model, which depicts the interrelationships among the constructs by determining path coefficients, is assessed and checked for the level of significance (T-statistics and p-value) by bootstrapping procedure. The other assessment measures, such as R^2 and Q^2 (usually measured by blindfolding process), are observed to test the model's explanatory power and predictive relevance, respectively. Further, the fitness of the model is assessed through fit parameters such as SRMR, NFI, d_{ULS}, d_{G}, and RMS_theta. Once the model is found fit and significant, the latent variable (construct) scores obtained during the parameter estimation process in PLS-SEM, are used directly for measuring the performance indices of service quality factors. The performance index of a service quality factor measures

Table 2
Extracted factors from Principal Component Analysis.

Factor	Service Quality Indicator	Symbol	Factor loading
Service Availability (SER_AVAIL)	Frequency of the Metro service available	M1	0.703
	Network Coverage	M2	0.651
	Start and end timings of Metro service	M3	0.523
	Waiting time on the platform	M17	0.610
	Regularity of the service	M18	0.521
	Punctuality against time	M19	0.509
Passenger Ease (PASS_EASE)	Ease of access to reach Metro stations	M4	0.434
	Ease of changeover to other modes from Metro station	M5	0.467
	Availability and operation of lifts and escalators	M6	0.497
	Ease of interchange from one line to another line within the Metro station	M7	0.522
	Ease of purchasing the ticket/cards	M9	0.638
	Smooth operation of toll gates for ticket validating at stations	M11	0.499
	Staff informative, helpful and available when needed	M21	0.625
	Performance of customer services	M22	0.545
	Attitude of Security Personnel	M23	0.711
	Comfort level inside Metro	M24	0.522
	Seat availability in Metro stations and at platforms	M27	0.524
	Convenience (facilities) at Metro stations	M31	0.553
Passenger Information (PASS_INF)	Clarity in the travel related information	M12	0.627
	Updated, accurate and reliable information in Metro stations	M13	0.749
	Updated, accurate and reliable information inside Metro	M14	0.746
	Information available on other communication technologies	M15	0.585
	Notification on operational changes through websites, mobile apps, and television	M16	0.532
Amenities (AMEN)	Availability of smart card facility	M10	0.510
	Availability of handrails or grab handles inside the Metro	M25	0.452
	Cleanliness in Metro stations	M28	0.749
	Cleanliness inside Metro	M29	0.759
	Lighting in the Metro system	M30	0.721
Safety and Security (SAFE_SEC)	Security against theft and aggression in Metro stations	M34	0.729
	Security against theft and aggression inside Metro	M35	0.703
	Safety against slipping, falling and accidents at Metro doors and escalators	M36	0.655
	Security to women against harassment	M37	0.628
Seamless Connectivity (SEAM_CON)	Interchange time from one line to another within the Metro station	M20	0.574
	Seat availability for person with disability (PwD), women and senior citizens inside Metro	M26	0.439
	Mobile network connectivity inside Metro system	M32	0.510
Environmental Impact (ENV_IMP)	Ecological environment outside Metro stations	M38	0.576
	Reduction in air pollutants emissions due to Metro system	M39	0.666
	Noise level due to trains, announcements, and advertisements at Metro stations	M40	0.822
	Noise level due to announcements inside Metro	M41	0.789
Overall Service Quality (OSQ)	Overall level of service	O1	0.863
	Overall level of satisfaction	O2	0.863

Kaiser-Meyer-Olkin Measure = 0.956.
Bartlett's Test of Sphericity (p-value < 0.001).

the performance level of transit services from the passengers' perspective (Shen et al., 2016).

5. Model results

5.1. Bayesian Networks (BN) results

The study generated an exploratory model by applying the BN approach on eight service quality factors obtained from PCA. The factor scores of each factor were rescaled (1 to 5) before implementing BN. The BN learning process involved 16 algorithms using the *bnlearn* package of *R* software.

Fig. 3 represents the BN structure obtained from the Hill-Climbing algorithm with the AIC score, selected as the most robust network structure. The total score for every arc resulted from all the 16 algorithms, is reported. The highlighted blue coloured arcs represent the total score greater than 11. The existence of arcs among the OSQ and all other service quality factors having a total score of 16, indicates direct relationships of all the service quality factors with the overall service quality and is in accordance with the previous studies (Allen et al., 2020; Fu et al., 2018; Liou et al., 2014). It is observed from the robust BN structure that the PASS_EASE factor plays an apparent role in influencing service quality directly and indirectly through other service quality factors such as PASS_INF, SER_AVAIL, SAFE_SEC, SEAM_CON, and AMEN factors. Interestingly, the ENV_IMP factor has an independent effect on OSQ.

Further, the robustness of selected BN structure has been examined by implementing bootstrap resampling process. Fig. 4 represents the robust network structure with the occurrence proportion of each arc in the bootstrap replicates. In the network, the arcs

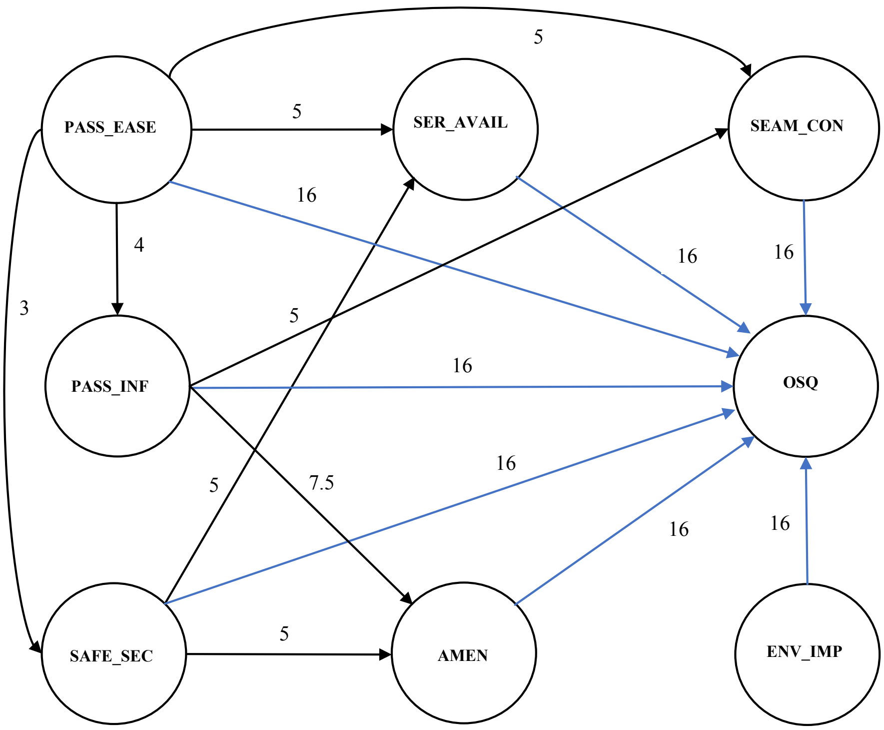


Fig. 3. Most robust Bayesian network structure.

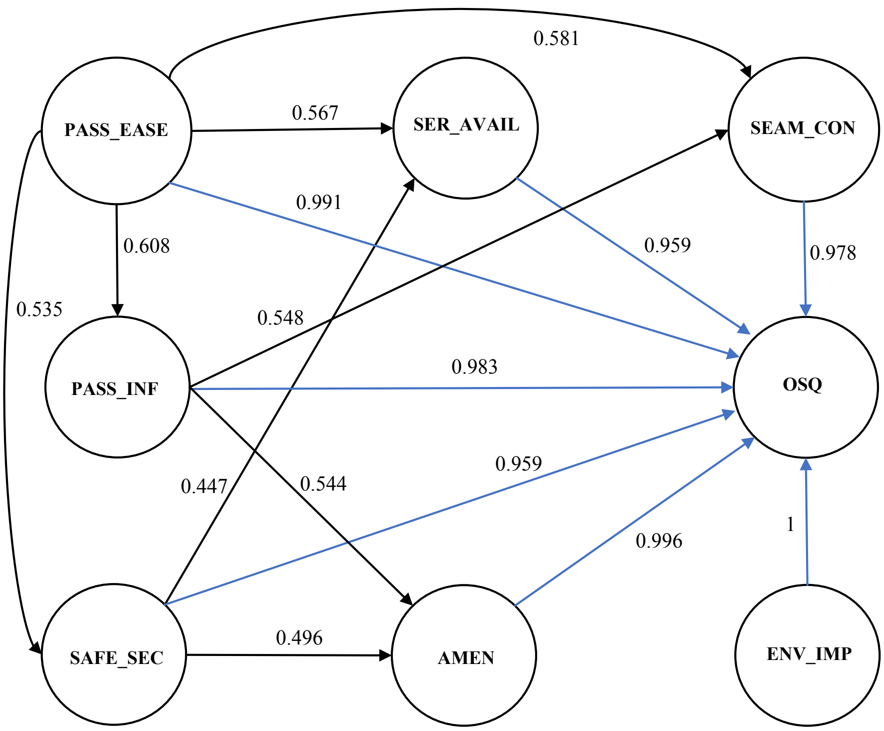


Fig. 4. Most robust Bayesian network with occurrence proportions.

with occurrence proportion near to 1 are considered to be robust while the arcs with occurrence proportion value less than 0.5 require a further check. All the blue coloured arcs have an occurrence proportion values near to 1, which indicates robust relationships in the chosen BN structure. Only two arcs, i.e., between SAFE_SEC and SER_AVAIL, and SAFE_SEC and AMEN, carry the

Table 3
Measurement model results.

Latent Variable (Construct)	Manifest Variable	Standard Loading	T Statistic	p-value	CR	AVE	Cronbach's α
Service Availability (SER_AVAIL)	M1	0.75	58.52	***	0.877	0.545	0.832
	M2	0.703	52.99	***			
	M3	0.68	48.29	***			
	M17	0.771	69.42	***			
	M18	0.773	66.94	***			
	M19	0.746	55.31	***			
Passenger Ease (PASS_EASE)	M4	0.647	43.34	***	0.900	0.431	0.880
	M5	0.689	52.22	***			
	M6	0.661	46.88	***			
	M7	0.647	43.97	***			
	M9	0.606	36.32	***			
	M11	0.547	31.61	***			
	M21	0.702	53.87	***			
	M22	0.67	42.80	***			
	M23	0.679	49.29	***			
	M24	0.672	51.54	***			
	M27	0.703	63.13	***			
	M31	0.641	48.21	***			
Passenger Information (PASS_INF)	M12	0.758	62.72	***	0.874	0.582	0.819
	M13	0.819	89.22	***			
	M14	0.83	100.85	***			
	M15	0.71	49.96	***			
	M16	0.688	46.97	***			
Amenities (AMEN)	M10	0.664	37.78	***	0.865	0.562	0.803
	M25	0.718	52.55	***			
	M28	0.811	77.86	***			
	M29	0.8	70.31	***			
	M30	0.746	50.38	***			
Safety and Security (SAFE_SEC)	M34	0.82	90.57	***	0.861	0.607	0.784
	M35	0.752	52.57	***			
	M36	0.793	78.47	***			
	M37	0.75	60.46	***			
Seamless Connectivity (SEAM_CON)	M20	0.742	59.01	***	0.778	0.538	0.604
	M26	0.743	58.16	***			
	M32	0.716	48.55	***			
Environmental Impact (ENV_IMP)	M38	0.734	58.81	***	0.889	0.668	0.831
	M39	0.77	65.92	***			
	M40	0.887	167.63	***			
	M41	0.868	137.15	***			
Overall Service Quality (OSQ)	O1	0.801	72.66	***	0.848	0.737	0.654
	O2	0.912	408.52	***			

CR – Composite Reliability, AVE – Average Variance Extracted, *** p-value < 0.001

proportion values below 0.5, thus require further analysis in PLS-SEM to check for their significance as well as relevance in the network structure.

5.2. PLS-SEM results

For analysing the exploratory model obtained from BN, the PLS-SEM model is built using the extracted interrelationships among service quality constructs (factors) in *SmartPLS Software (Version 3.0)*. The model incorporates seven service quality constructs described by 39 service quality indicators (i.e., M1 to M41 except for M8 and M33), and an 'Overall Service Quality (OSQ)' construct with two indicators (i.e., O1 and O2). Tables 3 and 4 show the measurement and structural model results.

The measurement model in PLS-SEM includes two essential tasks, i.e., examining the relationships of MVs (i.e., 39 indicators, O1 and O2) with their respective constructs, and checking the model for reliability and validity tests. Table 3 depicts the measurement model results. The findings show that all the indicators are significantly related to their respective constructs (p-value < 0.001), having the standard loadings greater than 0.6. However, loadings greater than 0.4 are acceptable for exploratory studies (Hulland, 1999; Usakli and Kucukergin, 2018). Therefore, the study attained acceptable indicator reliability. Composite Reliability (CR values > 0.7) and Cronbach's alpha (α values > 0.6) for each construct are greater than the threshold value of 0.6. It indicates satisfactory internal consistency reliability. For ensuring the convergent validity of each construct in the model, the Average Variance Extracted (AVE) value equal to or higher than 0.5 is acceptable. However, construct having AVE value > 0.4 still shows adequate convergent validity, only if its CR value is higher than 0.6 (Fornell and Larcker, 1981). In the model, all the constructs except the PASS_EASE construct (AVE value of 0.431 and CR value of 0.900) have higher AVE (> 0.5) values, representing satisfactory convergent validity. Each indicator has its standard loading larger than its cross-loadings, which signifies adequacy in discriminant

Table 4
Structural model results: Path coefficient between the constructs.

Path relation		Path coefficient	Standard error	T Statistics	p-value
PASS_EASE →	PASS_INF	0.582	0.017	33.85	***
PASS_EASE →	SER_AVAIL	0.509	0.017	29.35	***
PASS_EASE →	SAFE_SEC	0.478	0.019	24.05	***
PASS_EASE →	SEAM_CON	0.480	0.022	21.99	***
PASS_EASE →	OSQ	0.278	0.018	15.58	***
PASS_INF →	AMEN	0.639	0.019	32.30	***
PASS_INF →	SEAM_CON	0.422	0.021	18.78	***
SAFE_SEC →	AMEN	0.516	0.019	25.99	***
SAFE_SEC →	SER_AVAIL	0.497	0.019	24.46	***
SAFE_SEC →	OSQ	0.184	0.014	13.63	***
AMEN →	OSQ	0.088	0.014	6.13	***
SEAM_CON →	OSQ	0.128	0.017	7.58	***
SER_AVAIL →	OSQ	0.126	0.016	7.91	***
ENV_IMP →	OSQ	0.292	0.015	19.89	***

*** p-value < 0.001

validity among the constructs. Thus, the constructs and their related indicators adequately pass the reliability and validity checks.

The structural model in PLS-SEM examines path relationships among eight constructs. Table 4 represents the structural model results. A measure of collinearity, i.e., Variance Inflation Factor (VIF) values, has been examined before structural model analysis to ensure the absence of any biased-ness in the relationship coefficients. The VIF values obtained for all the indicators and constructs are within the acceptable limits, i.e., less than 5, ensuring no multicollinearity issue exists in the model. Concerning the path relations, except for the relationship of PASS_INF with OSQ, all the relationships are significant at 0.001 level of significance (Table 4). The two relationships (i.e., SAFE_SEC with SER_AVAIL, and SAFE_SEC with AMEN) whose occurrence proportion was below 0.5 in the robust BN structure (Fig. 4) have significant, non-zero and positive path coefficients (0.497 and 0.516) in the PLS-SEM model. Almost all the constructs, i.e., PASS_EASE, SER_AVAIL, AMEN, SAFE_SEC, SEAM_CON, and ENV_IMP, show positive path coefficients with OSQ and are significant at 0.001 level, with a direct influence on OSQ. Only the PASS_INF construct represents an insignificant relationship with OSQ, indicating no direct effect of PASS_INF construct on OSQ. The findings are as expected and accord the existing studies (Díez-Mesa et al., 2018). However, the contribution of PASS_INF is checked through its overall effect on OSQ.

Fig. 5 shows the final path analysis model with significant relationships. It is worth noting that the PASS_INF relationship with OSQ has been removed from the final path analysis model, as it indicated an insignificant path coefficient. The R^2 value of OSQ is

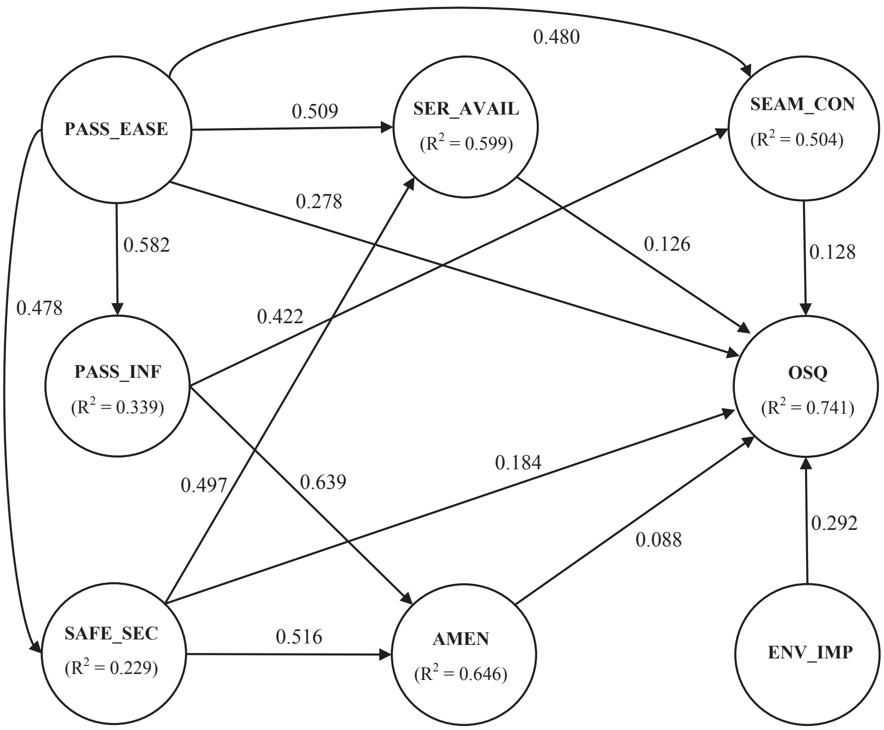


Fig. 5. Path analysis model with significant interrelationships.

Table 5
Correlation coefficient matrix of latent constructs.

Construct	SER_AVAIL	PASS_EASE	PASS_INF	AMEN	SAFE_SEC	SEAM_CON	ENV_IMP	OSQ
SER_AVAIL	1.000							
PASS_EASE	0.651	1.000						
PASS_INF	0.434	0.582	1.000					
AMEN	0.417	0.517	0.589	1.000				
SAFE_SEC	0.540	0.478	0.474	0.524	1.000			
SEAM_CON	0.473	0.609	0.502	0.451	0.418	1.000		
ENV_IMP	0.479	0.469	0.433	0.399	0.428	0.340	1.000	
OSQ	0.672	0.737	0.579	0.578	0.622	0.662	0.693	1.000

Table 6
Summary of goodness-of-fit of the model.

Model fit index	Observed Value	Acceptable Value
SRMR	0.064	< 0.08
d_{ULS}	0.923 (HI_{95} = 1.092)	$d_{ULS} < HI_{95}$ of d_{ULS}
d_G	0.131 (HI_{95} = 0.279)	$d_G < HI_{95}$ of d_G
NFI	0.896	≥ 0.90
RMS_theta	0.102	< 0.12

Table 7
Effects of service quality factors on “Overall Service Quality (OSQ)”

Factor	Direct Effect	Indirect Effect	Total Effect
SER_AVAIL	0.126	0.000	0.126
PASS_EASE	0.278	0.329	0.607
PASS_INF	0.000	0.110	0.110
AMEN	0.088	0.000	0.088
SAFE_SEC	0.184	0.108	0.292
SEAM_CON	0.128	0.000	0.128
ENV_IMP	0.292	0.000	0.292

observed as 74.1% in the model. It indicates that the combination of PASS_EASE, SER_AVAIL, PASS_INF, AMEN, SEAM_CON, SAFE_SEC, and ENV_IMP can explain 74.1% variance in OSQ construct in the model. An R^2 value of 0.75 is considered substantial (Henseler et al., 2016). Thus, the R^2 value in the study explains the substantial prediction accuracy of the model. Besides, measure of predictive relevance (Q^2) values for each endogenous construct is found greater than zero for all the endogenous constructs

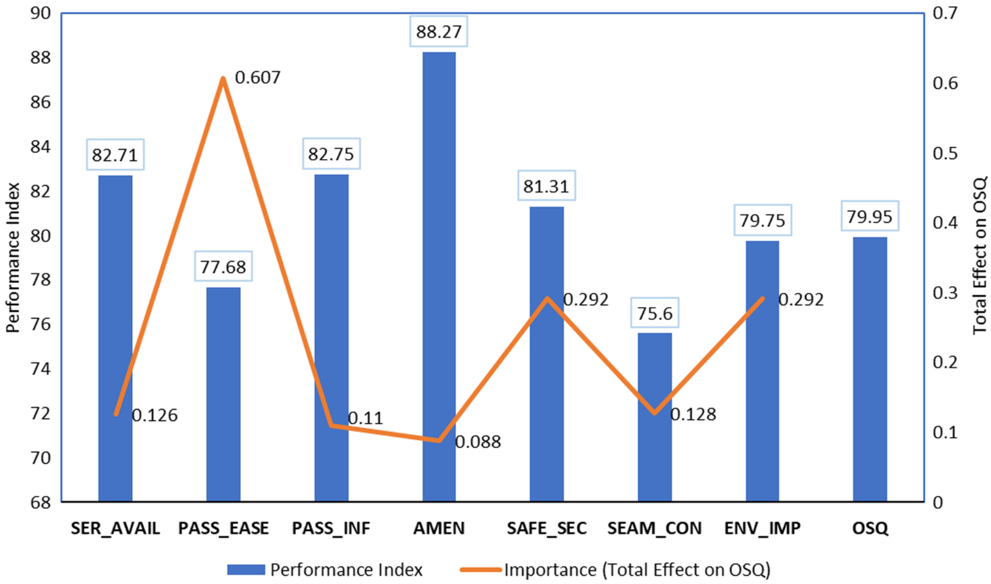


Fig. 6. Performance and Importance of service quality factors.

(PASS_INF: 0.196; SAFE_SEC: 0.138; SER_AVAIL: 0.264; AMEN: 0.233; SEAM_CON: 0.212; OSQ: 0.529), supporting the adequate predictive quality of the model.

Table 5 represents the correlation coefficient matrix between the latent constructs of PLS-SEM model. It implies that all the service quality constructs have a strong and positive correlation with OSQ. Inter-construct correlations are as expected and support the efficacy of PLS-SEM in exploring the interrelationships. For instance, the low correlation of ENV_IMP construct with other constructs (except OSQ) indicates that ENV_IMP has an independent and positive association with OSQ. Table 6 provides a summary of the goodness-of-fit assessment of the PLS-SEM model. The d_{ULS} and d_G values are observed to be below 95% quantile of the bootstrapped discrepancies (HI_{95}) (i.e., $d_{ULS} < HI_{95}$ of d_{ULS}, and $d_G < HI_{95}$ of d_G), accounting for good model fit. The NFI value is close to 0.90, representing the substantial model fit. The model achieved all the fit (approximate and exact) indices values within the acceptable limits, revealing the good fit of the model.

6. Discussion

6.1. Theory of interrelationships among service quality factors

The present study explored, analysed, and developed the interrelationships among service quality factors (constructs) through a robust BN and PLS-SEM methodology. The relationships extracted from BN are found suitable for PLS-SEM. The integrated approach has shown to be an appropriate approach for establishing the interrelationships among service quality factors of the MRTS. Table 7 illustrates the direct, indirect, and total effects of each service quality factors on OSQ. Some relationships, such as PASS_INF with OSQ is disqualified by PLS-SEM and is possible only with this methodological framework. However, PASS_INF is found to influence OSQ indirectly (indirect effect = 0.110) through SEAM_CON and AMEN factors. It affirms that all the factors have specific (direct or indirect or both) effect on OSQ, supporting the findings of prior research (Allen et al., 2020; Díez-Mesa et al., 2018; Eboli and Mazzulla, 2015; Fu et al., 2018; Liou et al., 2014; Zhang et al., 2019).

Among all factors, PASS_EASE has the most substantial influence on OSQ (total effect = 0.607). Interestingly, its indirect effect (0.329) is dominant and is through other factors such as PASS_INF, SER_AVAIL, SEAM_CON, and SAFE_SEC. It implies that a positive or negative perception towards indicators of PASS_EASE has a similar and sequential influence on the perception of other related factors and OSQ. The relationship of PASS_EASE with other related factors is illustrated as follows:

a. Ease of access to metro stations, transfers, interchanges, and ticket validation allows passengers to perceive a reasonable level of satisfaction on service frequency, punctuality, regularity, and waiting. This relationship has been proven to be consistent with the previous studies (De Oña et al., 2018; Deb and Ahmed, 2018; Wu et al., 2016) that comfort, convenience and accessibility aspects in Bus transit system are closely related to the punctuality and regularity of the service. It confirms the relationship of PASS_EASE with SER_AVAIL of any transit system (Metro or Bus) in any context (developed or developing nation).
b. Helpful staff and security personnel allow passengers to sense security against theft, aggression, accidents, and harassment (especially for women). Similar findings are attained by previous research (Díez-Mesa et al., 2018; Liou et al., 2014), which were carried out in developed nations. Thus, the relationship of PASS_EASE with SAFE_SEC is justified.
c. Informative staff and customer services help passengers to attain clarity in information, and updates while travelling. Liou et al. (2014) also highlighted the relationship between the 'courtesy of staff' and the 'passenger information' for the bus transit system in Taipei, Taiwan. These aspects support the relationship of PASS_EASE with PASS_INF.
d. Finally, the ease in interchange will have a positive influence on interchange time and seat availability in terminals and platforms, which allow PwD and Women to perceive excellent satisfaction inside Metro too. Also, the convenience of seat availability for PwD and Women inside Metro positively influences OSQ. Therefore, the relationship of PASS_EASE through SEAM_CON is also justified.

SAFE_SEC has the second highest influence on OSQ, with a total effect of 0.292. Safety and security for women have significant and primal importance in public transit systems, especially in Delhi, India. This factor requires attention since only nine percent female passengers sense safety and security in public transit of Delhi (UITP, 2014). The findings indicate that SAFE_SEC is related to SER_AVAIL, AMEN, and OSQ. A positive sense of safety and security (especially for women) will allow passengers to have a higher satisfaction towards Metro regularity, punctuality and frequency, and also on the amenities available. These findings accord the findings of Yanık et al. (2017), and van Lierop and El-Geneidy (2016), that were conducted for MRTS in developed nations. Therefore, an increase in the sense of safety and security can enhance the perceived satisfaction towards the service frequency, reliability, cleanliness, and lighting, etc., supporting the relationships with SER_AVAIL and AMEN.

The case of PASS_INF, having no direct effect on OSQ, has shown that the provision of updated, reliable, and accurate travel information will have a positive impact on interchange time because passengers can direct themselves towards proper directions. Thus, if PASS_INF improves, then the satisfaction on SEAM_CON can increase. A similar effect is observed in the relationship with AMEN. For example, a passenger avails the smart card facility only when he/she perceives that the travel information is updated, reliable, and notified. Hence, the relationships with SEAM_CON and AMEN is justified. Similar results were found by Díez-Mesa et al. (2018), where the 'information' factor has only an indirect effect on overall service quality through other factors.

The SER_AVAIL factor is directly connected to the OSQ because the higher availability of Metro service, i.e., its punctuality, regularity, and frequency, will improve passengers' level of satisfaction. The literature evident that this factor has been represented as the basic and central dimension for assessing the overall satisfaction towards transit service provision (Díez-Mesa et al., 2018; Eboli and Mazzulla, 2008; Morton et al., 2016). Also, higher satisfaction on amenities such as smart cards, guard rails, lighting, etc. will allow passengers to feel comfortable. It indeed increases their perception of OSQ. Similar is the relationship between SEAM_CON factor and OSQ. Functional connectivity in terms of interchanges and mobile networks can improve the passengers' perception of the level of service.

Finally, the ENV_IMP factor has an independent and direct effect on OSQ. Passengers perceive environmental impact aspects (e.g., air pollution, noise level) as a separate factor and entail significant effect (0.292) on OSQ. It shows the passengers' concern about environmental issues due to worsened air quality in the neighbourhoods of Delhi. Also, it attributes to the fact that Delhi Metro is an electric-driven transit system that earned carbon credits in reducing CO_2 emissions. However, this aspect requires significant attention when noise and ecological environment outside Metro stations are a matter of concern. This finding is in contrast to Díez-Mesa et al. (2018) study and justifies the need for context-specific service quality models.

In summary, these interrelationships identified from the integrated BN and PLS-SEM methodology for developing the service quality model agree with real-world scenarios. Thus, the present study supports the significance of using the integrated methodological approach in identifying the hidden interrelationships among the service quality factors and developing new theories in the transit service quality arena.

6.2. Performance of service quality factors

Fig. 6 illustrates the performance indices of service quality factors that are translated into the centesimal system, along with their importance (total effect) on OSQ. All the performance indices are relatively higher than 75, indicating the moderate satisfaction of passengers towards the performance of transit service in almost all the aspects. However, some improvements are still required in terms of safety and security, passenger ease, and seamless connectivity. Besides, some gaps are identified between the performance and importance of service quality factors. For instance, the AMEN factor has a relatively high performance index but has very low importance in affecting overall service quality. These gaps are problems where the transit agencies should pay attention for the improvement of service quality of Delhi Metro. PASS_EASE, for example, has a greater gap, indicating that immediate improvement measures for ease of access, comfort, and convenience are required. Besides, SER_AVAIL and PASS_INF are advantages to the Delhi Metro service, which require consistency. Consequently, the performance indices assist in identifying the problems in transit service in a realistic manner.

The overall service quality index of Delhi Metro is 79.59, which is still less than 85.52 of Suzhou MRTS in China (Shen et al., 2016). The performance of the service quality of Delhi Metro has to be continuously improved to fill the gaps and increase its ability. Transit operators must consider the study findings for uplifting the position of Delhi Metro in global standards. Thus, the performance indices obtained from PLS-SEM seem straightforward and provide insights for practical interpretation. These indices are also helpful as a prescription tool for planners, policymakers, and researchers to estimate and compare the scores for other transit systems in India and worldwide.

7. Conclusions

The public transit usage relies significantly upon passengers' perception of its service quality. Profoundly reasoned passengers' perspectives in terms of service quality factors guide the transit providers to undertake constructive measures based on the interrelationships model. These models transform and convert the unobserved factors of service quality into strategic actions. However, limited knowledge of the interrelationships among service quality factors has attracted researchers worldwide to explore this arena. The present work makes the contribution to the literature by employing an integrated approach that involves Bayesian Networks (BN) and PLS-SEM for establishing interrelationships between service quality factors of Delhi Metro. This study demonstrates the usefulness of PLS-SEM as a powerful tool to test, analyse, and develop new theories in the service quality literature. In the integrated methodology, BN and PLS-SEM act as complementary to one another. In the absence of prior knowledge, the BN builds an exploratory model by learning the relationships from the available data; the PLS-SEM tests and analyses the exploratory model from a prediction perspective and helps in theory development.

The entire analysis involved three stages. Firstly, the passengers' perception of 41 service quality indicators and 2 OSQ indicators were factor analysed using Principal Component Analysis (PCA). Secondly, the eight extracted factors (7 service quality factors and OSQ factor) have been taken as input in the BN to learn the interrelationships by implementing 16 algorithms. The BN structure learnt from the Hill-Climbing algorithm with AIC score was selected as the most robust network structure. Thirdly, the exploratory model learnt from BN was tested and analysed in PLS-SEM. The PLS-SEM model has confirmed that most of the service quality factors have a non-zero, positive, significant, and direct influence on OSQ. The study identified some essential and interesting relationships of service quality factors that not only influence OSQ but also interrelate with each other. It indeed has proved the efficacy of the proposed integrated approach.

The interrelationships among service quality factors and their performance reveal significant policy implications for transit providers to enhance service quality and consequently increase transit ridership. The necessary improvements in and around transit stations are as follows:

- Ease of access/egress through sustainable modes of transport such as e-rickshaw/cycling should be improved. Such improvements will also allow passengers to perceive aspects of passenger information, service availability, safety and security, and seamless connectivity in a better way.

- Providing real-time transit schedules in the mobile applications will allow passengers to plan their trips.
- Passengers appreciate the existing frequency, regularity, and punctuality of Metro service. The sense of these aspects has to be maintained in the future years for better service quality.
- Adequate enforcement, such as employment of security personnel at isolated areas around the transit station, should be provided for the safety and security of passengers (especially for women).
- Proper lighting and cleanliness in and around transit stations are necessary to enrich the Metro system services.
- Passengers perceive mobile network connectivity inside Metro as a significant concern. This aspect needs to be addressed soon for better service quality.
- Adequate plantations outside transit stations and at the access/egress ends will reduce air pollution and disseminate noise pollution.

Overall, the study findings highlight the shortcomings of the Delhi Metro service. Also, the service quality model delivers insightful knowledge about the significant service quality aspects which influence the passengers' decision of travelling in Delhi Metro. This knowledge can assist the transit officials and policymakers in formulating effective policies and investing efficiently for enhancing Metro service quality. This way, they can retain the existing passengers and attract potential ones, consequently increasing the ridership of the Metro system. Hence, the present study explored, analysed and established the theory of interrelationships among service quality factors for MRTS of a city from developing nation, i.e., Delhi, India, using the robust BN and PLS-SEM approach. Nevertheless, further studies could reconfirm and support the identified model for any MRTS in developing nations.

CRediT authorship contribution statement

Jyoti Mandhani: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing - original draft. **Jogendra Kumar Nayak:** Investigation, Resources, Data curation, Writing - review & editing. **Manoranjan Parida:** Writing - review & editing, Visualization, Supervision.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2020.08.014.

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