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Original Article

BAYESIAN NETWORKS AND STRUCTURAL EQUATION MODELLING TO INVESTIGATE THE PASSENGERS' PERCEPTIONS IN HIGH-SPEED RAIL SYSTEMS

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Highlights:
- HSRS passengers' perceptions were investigated;
- BN and SEM were applied to the survey data;
- the direct links from image to trust and loyalty, from trust to perceived value, from perceived value to satisfaction, and from satisfaction to loyalty were empirically supported;
- in the best-case scenario, 97% of the passengers were determined to be loyal to the company while it was found 10% in the worst-case scenario.

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Abstract. Ensuring sustainability in the global world today depends on perception management as well as financial management. In order to manage the perceptions, which are inherently latent variables as they are measured indirectly through their indicators, they must be accurately handled and modelled comprehensively. In the present study, a hybrid technique combining Bayesian Networks (BN) and Structural Equation Modelling (SEM), which are regarded as causal models, was used to investigate the perceptions of High-Speed Rail System (HSRS) passengers. In order to provide insight into the customer retention strategy for HSRS, the analyses were performed on the survey data gathered from the frequent users of HSRS operating between 2 cities of Turkey. After the measurement model of the perception variables through SEM was established, the relationships between the variables were learned using BN knowledge extraction algorithms. As a result, relationships from image to trust and loyalty, from trust to perceived value, from perceived value to satisfaction, and from satisfaction to loyalty were determined. Final interpretations were made in terms of risk management with the help of the probabilistic predictive ability of the BN by setting evidence on the satisfaction levels of the perceptions.

Keywords: Bayesian networks, image, loyalty, perceived value, satisfaction, transportation, trust.

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Notations

ARACNE – algorithm for the reconstruction of accurate cellular networks;
AVE – average variance extracted;
BDe – Bayesian–Dirichlet equivalent;
BN – Bayesian networks;
BS – Bayesian search;
C2C – customer-to-customer;
CFA – confirmatory factor analysis;
CFI – comparative fit index;
CLF – common latent factor;
CPT – conditional probability table;
CR – composite reliability;
d.f. – degrees of freedom;
DAG – directed acyclic graph;
EFA – explanatory factor analysis;
GeNIe – graphical network interface;
HSRS – high-speed rail system;
KMO – Kaiser–Mayer–Olkin;
LRT – light rail transit;
NFI – normed fit index;
NNFI – non-NFI;
PLS – partial least squares;
RMSEA – root mean squared error of approximation;
SEM – structural equation modelling;

SQ – service quality;
SRMR – standardized root mean squared residual;
TLI – Tucker–Lewis index.

1. Introduction

HSRS improve the quality of rail services and provide greater customer satisfaction. They also help to create socioeconomically balanced societies (He *et al.* 2016). For a train to be called a high-speed train in commercial service, it must have a speed of at least 250 km/h. Today, HSRS are used in some European countries, such as Italy, Germany, and Spain, as well as in Japan, China, and South Korea. The Turkish State Railways started building high-speed railways in 2003; the 1st section of the high-speed train line was put into service between Ankara and Eskisehir in 2009 (Akyıldız Alçura *et al.* 2016).

It is inevitable that HSRS compete with other transport systems (highway and airway) to attract customers. Therefore, there must be a reason for passengers to choose HSRS over other transport systems. Identifying factors that influence passenger satisfaction and loyalty will offer managers an opportunity to optimize the use of limited resources and to keep loyal customers in the system and, at the same time, attract new ones. Sirohi *et al.* (1998) state that understanding the loyalty intentions and determinants of existing customers is an essential basis for identifying the best retailer activities.

In today's globalizing world, classical financial performance measurements and management of service companies like HSRS have gradually been replaced by the evaluation and management of customer perceptions. There are intense researches on main customer perceptions focusing on customer satisfaction, loyalty, image, trust, and perceived value for all of the sectors including transport. The study aims to investigate the relationships among satisfaction, loyalty, image, trust, and perceived value, which are passengers' perceptions related to the service provided in HSRS operating between Ankara and Eskisehir. SEM and BN can be used to evaluate the relationships between variables. After investigation of the related literature on modelling customer perceptions, the dominating use of SEM was detected since perception variables are latent variables that cannot be observed or measured directly, but can be measured through indicator variables by forming a measurement model. One of the most crucial stages of the SEM is to determine hypotheses for causal links of factors or latent variables, even if a strong measurement model is provided with proper psychometric properties. The consequences of the model misspecification may lead to misleading inference for the whole model with direct and indirect relationships. For each relationship, a persuasive theoretical background, as well as empirical supports, is needed. However, some controversial issues may occur in model building. For instance:

- while Chiou (2004) and Martínez (2015) stated that trust has a positive effect on satisfaction; Schlesinger *et al.* (2017), Akamavi *et al.* (2015), Chen & Phou (2013), and Jang *et al.* (2013) indicated that satisfaction has a positive effect on trust;
- Chi & Qu (2008), Ryu *et al.* (2012), Brown & Mazzarol (2009), and Alves & Raposo (2007) determined that image has a positive effect on satisfaction while Jani and Han (2014) stated that satisfaction has a positive effect on image;
- Kim *et al.* (2012) and Chiou (2004) indicated that trust has a positive effect on value while Chen & Chang (2012) stated that value has a positive effect on trust, on the subject of their studies.

Even if there is a theory-driven model, the researchers would like to see its reflection in the data, or else they would like to get help from the data. At this point, the hybrid approach integrating the SEM with BN may help the researchers to find out the directions of the relationships among the factors. This approach can also make the model interpretations useful for a particular purpose.

In this study, the relationships among the satisfaction, loyalty, image, trust, and perceived value for HSRS transportation service were learned by knowledge extraction algorithms of BN instead of causal link theory or by previous studies in the literature. In addition, by setting evidence on the specific states of the perception variables, it was examined how the other variables were affected by it. In this regard, this study contributes to the literature by taking the classical SEM method to the next level by examining how the variables affect each other in a percentage way as a result of different scenarios. Our case study for HSRS brings together the advantages of ability to reveal the relationships of BN with proper measurement model of the perception variables of SEM.

This study contributes to transportation literature with learning the relationships between the customer perceptions of passengers with the knowledge extraction algorithms. In the existence of controversial issues such as "Does trust has a positive effect on satisfaction or vice versa?", the knowledge extractions algorithms may help the researchers to find out the direction of the relationships. In addition, the approach used in this study can provide prior information to researchers by revealing relationships that are not included in the literature through learning from data. This is especially crucial for the SEM studies because the consequences of the model misspecification may lead to misleading outcomes for the entire structure.

This article is organized as follows: Section 1 is introduction, Section 2 shows the literature review of the factors used in this study in terms of their definitions, relationships between them, and previous studies linking SEM with BN. Methodology is given in the Section 3. General information about the data and the variables are presented in the Section 4. In the Section 5, measurement model results and results gained by analysing the BN model are given. Managerial recommendations and conclusions are provided in the Section 6.

2. Literature review

Corporate image can be expressed as the impression, the thought, the understanding, and values that people have left about people or institutions willingly or unwillingly. The image may represent the general situation of the organization as well as values that may remind the business as perceptions of customers regarding the product or service offered (Demir 2012). Consequently, the corporate image can be accepted as a collection of values that are formed as a result of impressions and experiences obtained from the product or service purchased by the customer using information obtained from various sources related to a brand (Lin, Lu, 2010). Trust in commercial relations is defined as the reliance on the reliability and integrity of the other party (Aydin, Özer 2005). Because the customer carries risk in his/her decisions, trust is a tool that facilitates decision making in case of confusion (Eren, Erge 2012; Lewis, Weigert 1985). Trust; believing in the brand before the intention to buy a brand. At this point, the goodwill of the customer is also essential. The customer considers a brand as a personified entity and expects a safe and, at the same time, the long-term reaction from that asset. It assumes that the customer will be happy if this expectation is met. Trust, on the other hand, is a process that consumers must go through to build a positive relationship (Swaen, Chumpitaz 2008). Perceived value is the customers' overall assessment of the net value of the service received, based on what the customer has received (benefits provided by the service) and what has been given to the customer (based on cost or sacrifice in obtaining and using the service). In every sector where intensive competition conditions are experienced, organizations have to give importance to customer satisfaction in order to keep their existing customers and win new ones (Yalçin, Koçak 2009). The attitude that a consumer develops as a result of evaluating the consumption experience with a particular product is called consumer satisfaction or dissatisfaction. Consumer satisfaction is a crucial element of the repurchase decision (Gölbaşı-Şimşek, Noyan 2009; Kaşmer 2005). Customer satisfaction is the most effective element of the company or brand in communication with the target market and, at the same time, the lowest cost. A satisfied customer can tell his or her satisfaction to potential customers, while an unsatisfied customer can tell his or her complaints and dissatisfaction with those around him or her (Dubrovski 2001). Customer loyalty has become increasingly important both in marketing efforts and management practices, especially since 1990. This importance stems from customers' choice of products and services. Businesses that can generate customer loyalty has a significant advantage over their competitors (Çatı, Koçoğlu 2008). The SEM studies, which used the image, trust, perceived value, satisfaction, and loyalty in their research and the relationships between the factors, the study areas of the related articles, and the sample sizes are summarized in Table 1.

The SEM has gained the most attention in the context of the causal models with factors. However, there have been very few studies and 2 different approaches where the SEM and the BN are handled together.

Pre-processing the SEM for the BN, is the 1st approach. In this approach, the BN was applied right after the SEM process. In other words, the BN learning algorithms do not contribute to the determination of the relationships between the factors. Chanpariyavatevong *et al.* (2021) studied on determining the impact of critical factors on airline loyalty in Thailand by implementing BN derived from SEM. Deng *et al.* (2021) applied SEM analysis to examine the factors affecting consumers' online search intention and willingness to purchase, and the relationship between them. Then, they used a BN to quantitatively analyse the degree of influence of each factor. Gerassis *et al.* (2019) implemented SEM-BN model to analyse the risk of accidents in complex blasting operations. By using this hybrid method, they examined different scenarios setting evidence on the different states of the latent variables. Li *et al.* (2018) developed an integrated approach by combining the SEM and the BN. They developed SEM-BN models to explore the complex relationships among the factors. Gupta & Kim (2008) have also linked the SEM to the BN for decision support for customer retention in a virtual community. Xu *et al.* (2016) applied SEM to improve the model structure for the BN. They showed that this method decreases the necessity for expert knowledge. Besides, they explained that this method not only creates more reasonable models for the BN models, but also improves the accuracy and the reliability of the BN models. Tao & Fan (2017) proposed a model for which the empirical analysis was carried out in 3 stages that combine CFA, the SEM, and the BN. Hsu *et al.* (2013) proposed an integrated BN approach that uses the SEM for discovering the causal relationships, which are afterward used as the BN network structure to predict the e-learning attendance level. The SEM was used to help the BN in finding a suitable network structure for estimation. Based on the results, they determined that compared with back-propagation neural networks and classification and regression trees, the SEM-BN gave better results. Addae *et al.* (2019) applied PLS-SEM to analyse empirical data collected for the study, and the findings from the PLS-SEM model were used as an input for the BN for personalized adaptive cybersecurity. Wu *et al.* (2015b) applied the BN-SEM hybrid model to help the companies to make the instructions better for future management practices.

Pre-processing the BN for the SEM is the 2nd approach. The BN is combined with the SEM in the way of learning information or model from the data. The BN learning algorithms contribute to the determination of the relationships between the factors. It is a data-driven process and may help the researchers in the way of finding the potential relationships among factors. Pegolo *et al.* (2020) implemented hill-climbing algorithm, which is one of the BN structure learning algorithms, to infer network structure to estimate SEM. They applied 50000 bootstrap samples to decide for the final network. Xu *et al.* (2020) aimed to improve the SQ of Beijing metro (China) combining the BN and SEM methods. They 1st aimed to select a robust network structure by using BN structure learning algorithms.

Table 1. The relationships between image, satisfaction, trust, value, and loyalty according to the previous SEM studies

Relationship*	Area	Reference	Sample size (totally)
IM → LO	education	Alves & Raposo (2007)	2687
IM → LO	mobile telecommunication market	Aydin & Özer (2005)	1662
IM → LO	education	Brown & Mazzarol (2009)	373
IM → LO	transportation	Brunner *et al.* (2008)	941
IM → LO	transportation	Dwita & Megawati (2022)	198
IM → LO	tourism	Hasan *et al.* (2022)	170
IM → LO	hotel	Jani & Han (2014)	529
IM → LO	tourism	Loureiro & González (2008)	679
IM → LO	green marketing	Martínez (2015)	382
IM → LO	industrial business market	Mustonen *et al.* (2016)	121
IM → LO	tourism	Wallin Andreassen & Lindestad (1998)	600
IM → TR	restaurant	Chang (2013)	600
IM → TR	tourism	Chen & Phou (2013)	428
IM → TR	banking	Flavián *et al.* (2005)	633
IM → TR	tourism	Loureiro & González (2008)	679
IM → TR	green marketing	Martínez (2015)	382
IM → TR	education	Schlesinger *et al.* (2017)	1000
IM → TR	tourism	Su *et al.* (2017)	314
SA → LO	transportation	Akamavi *et al.* (2015)	286
SA → LO	education	Alves & Raposo (2007)	2687
SA → LO	tourism	Wallin Andreassen & Lindestad (1998)	600
SA → LO	education	Brown & Mazzarol (2009)	373
SA → LO	transportation	Brunner *et al.* (2008)	941
SA → LO	restaurant	Chang (2013)	600
SA → LO	internet	Chang & Chen (2008)	334
SA → LO	tourism	Chen & Phou (2013)	428
SA → LO	transportation	Chi & Qu (2008)	345
SA → LO	internet service providers	Chiou (2004)	209
SA → LO	internet service providers	Chiou (2004)	209
SA → LO	internet	Choi *et al.* (2008)	247
SA → LO	transportation	Chou & Kim (2009)	418
SA → LO	transportation	Chou *et al.* (2014)	1235
SA → LO	marketing and service management	Coelho & Henseler (2012)	2104
SA → LO	internet	Cyr *et al.* (2010)	270
SA → LO	transportation	Dwita & Megawati 2022	198
SA → LO	service industry	Dagger & O'Brien (2010)	376
SA → LO	transportation	Elkhani *et al.* (2014)	309
SA → LO	internet	Flavián *et al.* (2006)	351
SA → LO	service industry	Gustafsson & Johnson (2004)	260
SA → LO	online shopping	Chang & Wang (2011)	330
SA → LO	transportation	Hanafiah & Asyraff (2023)	250
SA → LO	tourism	Hasan *et al.* (2022)	170
SA → LO	transportation	Jang *et al.* (2013)	227
SA → LO	hotel	Jani & Han (2014)	529
SA → LO	transportation	Jomnonkwao *et al.* (2015)	2554
SA → LO	quality management	Jun *et al.* (2006)	407
SA → LO	internet	Kim *et al.* (2002)	14594
SA → LO	e-commerce	Kim *et al.* (2011)	340
SA → LO	tourism	Kim *et al.* (2010)	335
SA → LO	mobile services	Kuo *et al.* (2009)	387

End of Table 1

Relationship*	Area	Reference	Sample size (totally)
SA → LO	restaurant	Lee *et al.* (2009)	475
SA → LO	tourism	Lee *et al.* (2008)	472
SA → LO	online shopping	Lin & Sun (2009)	200
SA → LO	internet	Lin & Lee (2006)	200
SA → LO	mobile phone	Liu *et al.* (2011)	311
SA → LO	tourism	Loureiro & González (2008)	679
SA → LO	green marketing	Martínez (2015)	382
SA → LO	transportation	Minser & Webb (2010)	2439
SA → LO	transportation	Mohamad (2022)	360
SA → LO	service industry	Mollenkopf *et al.* (2007)	464
SA → LO	tourism	Nam *et al.* (2011)	378
SA → LO	tourism	Pereira *et al.* (2016)	3188
SA → LO	business	Rauyruen & Miller (2007)	306
SA → LO	restaurant	Ryu & Han (2011)	298
SA → LO	education	Schlesinger *et al.* (2017)	1000
SA → LO	transportation	Shen *et al.* (2016)	813
SA → LO	marketing	Suh & Youjae (2006)	1940
SA → LO	transportation	Sun *et al.* (2013)	498
SA → LO	internet	Teng (2010)	865
SA → LO	coffee shops	Walsh *et al.* (2011)	274
SA → LO	transportation	Wen *et al.* (2005)	600
SA → LO	service industry	Yee *et al.* (2010)	210
SA → LO	transportation	Yoon & Uysal (2005)	148
SA → LO	hospitality	Yoon *et al.* (2010)	444
SA → LO	tourism	Yüksel, A., Yüksel, F. (2007)	241
SA → LO	transportation	Zhang *et al.* (2019)	4702
SA → LO	internet	Zhou & Lu (2011)	223
TR → VA	internet service providers	Chiou (2004)	209
TR → VA	shopping	Kim *et al.* (2012)	513
TR → VA	web engagement	Shiu *et al.* (2015)	1845
TR → VA	service providers	Sirdeshmukh *et al.* (2002)	377
TR → VA	online C2C marketing	Wu *et al.* (2015a)	261
VA → SA	tourism	Wallin Andreassen & Lindestad (1998)	600
VA → SA	education	Brown & Mazzarol (2009)	373
VA → SA	restaurant	Chang (2013)	600
VA → SA	tourism	Chen, C.-F., Chen, F.-S. (2010)	477
VA → SA	internet service providers	Chiou (2004)	209
VA → SA	marketing and service management	Coelho & Henseler (2012)	2104
VA → SA	online shopping	Chang & Wang (2011)	330
VA → SA	tourism	Hasan *et al.* (2022)	170
VA → SA	hospitality	Kassinis & Soteriou (2003)	104
VA → SA	transportation	Lai & Chen (2011)	763
VA → SA	transportation	Parahoo *et al.* (2014)	169
VA → SA	airlane service	Park *et al.* (2006)	501
VA → SA	restaurant	Ryu *et al.* (2012)	300
VA → SA	transportation	Shen *et al.* (2016)	813
VA → SA	transportation	Sun *et al.* (2013)	498
VA → SA	transportation	Wen *et al.* (2005)	600
VA → SA	hospitality	Yoon *et al.* (2010)	444
VA → SA	transportation	Zhang *et al.* (2019)	4702

**Notes:* IM – image; TR – trust; VA – perceived value; SA – satisfaction; LO – loyalty.

Then they validated and evaluated the network structure with SEM. Duarte *et al.* (2015) proposed combining the power of the existing BN learning algorithms with the statistical rigor of the SEM. Yoo & Oh (2013) applied the combination of the BN and the SEM. In their study, it was shown that combining these 2 methods enable building a data-driven prediction model with the factors. Díez-Mesa *et al.* (2018) applied a 2-step process that combines the BN and the SEM techniques to model SQ in the Metropolitan LRT Service of Seville (Spain). In this study, the proposed approach was applied to extract and confirm the possible relationships among the LRT service factors and how they relate to the overall perception of the SQ, directly from the data without the preceding knowledge. For this end, after a network was learned from the data by BN learning algorithms, they used SEM to test the validity of the relationships. As a result, they determined that the model designed by the algorithms provided a good fit to the data. Duering *et al.* (2013) and Mengoli *et al.* (2017) implemented the combination of the BN and the SEM in the medical field. Hsu *et al.* (2009) proposed an integrated BN that adopts the SEM to predict tourism loyalty. Jakobowicz & Derquenne (2007) applied the BN-SEM approach for building the structural model in the marketing area. Töpner *et al.* (2017) made an application in genetics using the combination of the BN and the SEM. Jiang & Mahadevan (2009) presented a methodology that integrated the BN and the SEM to make use of multiple levels of data for hierarchical model validation. Zheng & Pavlou (2010) used the BN and the SEM to find out the relationships among the variables. Yoo (2018) proposed an approach called probabilistic-SEM that the justified-SEM model was re-evaluated in the BN.

3. Methodology

SEM and BN are both graphical techniques, and combining these 2 techniques has been a popular in recent years. Making the connection between them provides an alternative technique for analyses to the SEM researchers. By having a BN to work with, the SEM researchers can also have a more functional predictive model, with the help of the posterior probabilistic side of the BN.

3.1. Structural equation modelling

The SEM technique helps to explain the relationships among factors by examining the structure of the interrelationships shown by a series of equations. The SEM examines more than one relationship at once apart from the other multivariate statistical techniques. Thus, SEM is a technique that tests a set of hypotheses and considers all likely information (Hair *et al.* 2009). The model consists of a measurement model and a structural model. The former evaluates the items as linear functions of the factors (Irtema *et al.* 2018), and the latter shows the directions and the strengths of the relationships of the factors.

The general model is explained as follows (Jöreskog, Sörbom 1978): Let $\eta' = \left(\eta_1, \eta_2, \ldots, \eta_m\right)$ be the dependent variables and $\xi' = \left(\xi_1, \xi_2, \ldots, \xi_n\right)$ be the independent variables and, the mathematical description of structural relationships is given in equation:

$$\mathrm{B} \cdot \eta = \Gamma \cdot \xi + \zeta, \tag{1}$$

where: $B\left(m \times m\right)$ and $\Gamma\left(m \times n\right)$ are coefficient matrices and $\zeta' = \left(\zeta_1, \zeta_2, \ldots, \zeta_m\right)$ is a vector of random residuals; the vectors η and ξ are latent structures that is not observed directly; the observed vectors are $y' = \left(y_1, y_2, \ldots, y_p\right)$ and $x' = \left(x_1, x_2, \ldots, x_q\right)$, so that the formulas of y and x are given as follows:

$$y = \Lambda_y \cdot \eta + \varepsilon; \tag{2}$$

$$x = \Lambda_x \cdot \xi + \delta, \tag{3}$$

where: ε and δ are errors of measurement vectors in y and x, respectively; $\Lambda_y\left(p \times m\right)$ is regression matrix of y on η; $\Lambda_x\left(q \times n\right)$ is regression matrix of x on ξ; Equation (1) constitutes the structural model while Equations (2) and (3) constitutes the measurement model. Therefore, the measurement model can be given in a compact form as follows:

$$z = \Lambda \cdot f + e, \tag{4}$$

where: $z = \left(y', x'\right)'$, $f = \left(\eta, \xi\right)'$, and $e = \left(\varepsilon', \delta'\right)'$.

The SEM is confirmatory rather than exploratory since the researcher builds the structure by defining the directional effects among variables. CFA, which includes sensible constraints on parameters and excludes forced ones of EFA, is a special case of the SEM used for the measurement model estimation. There are many model goodness-of-fit indices to evaluate how well the data fit a proposed SEM model. 2-index representation strategy is proposed by Hu & Bentler (1999) by using the combination of NNFI or TLI, RMSEA or CFI along with SRMR to assess the goodness- of-fit of the model. It is the combination of the rules as SRMR ≤ 0.09 and NNFI ≥ 0.96, or SRMR ≤ 0.09 and RMSEA ≤ 0.06, or SRMR ≤ 0.09 and CFI ≥ 0.96, to provide a good model fit (Hooper *et al.* 2008). The SEM has been used in different fields, and currently, the technique is firmly established and frequently used in transportation (De Oña *et al.* 2015).

3.2. Bayesian networks

BN also called "belief networks" (Cheng *et al.* 1997), "Bayes networks" (Reed 1988), "Bayesian belief networks" (Sakellaropoulos, Nikiforidis 2000), or "decision networks" (Castelletti, Soncini-Sessa 2007; Heckerman 2008; Korb & Nicholson 2010; Zhu & Deshmukh 2003) in the literature are graphical models that powerfully visualize the joint probability distribution for a broad variables set. The concept of the BN was 1st suggested by Pearl (1985). It is a method that visually presents the conditional probabilities of all variables in a given network and runs well even with the small sample size (MacAllister 2018). The BN include nodes and arcs; the former represents the variables, and the latter represents the conditional dependencies among the variables and indicates the presence of the causal effects between linked variables (Tonda *et al.* 2013). BN is split into 2 components that correspond to the qualitative and quantitative descriptions of the network structure. The qualitative structure is a DAG that consists of a set of nodes that represent the variables and a set of directed arcs that demonstrate the existence of causal relationships among the variables. DAG is also known as loopless graph because the causal relationships never go back to where the arrows 1st start. A CPT, which is the 2nd component of BN, explains the likelihood of a node's states given the node's present predecessors. CPT specifies the conditional probability for each variable, and it is the variable that is an exact expression for the strength of causal impact between the variables (Xu *et al.* 2016). A key characteristic of BN is its ability to reduce the joint probability distribution of the model, which is typically intractable and difficult to assess, into a series of conditional probabilities via the application of the chain rule given in equation:

$$P\left(X_1, X_2, \ldots, X_n\right) = \prod_{i=1}^{n} P\left(X_i \mid pa\left(X_i\right)\right), \tag{5}$$

where: X_i (i = 1, 2, ..., n) is the variable; $pa(X_i)$ are the parents of node X_i (Pearl 1985).

In order to determine the network structure, various structure learning algorithms were developed to reduce computational complexity while still learning the correct network (Scutari 2010). Constraint-based, score-based, hybrid, and the local discovery algorithms are the types of the structure learning algorithms. These algorithms can also be used to extract knowledge from the data to achieve prior information about the network structure. By handling a specific state of any variable in the network, that is, setting evidence to a specific state, the marginal probability values of the other variables in the network could be reached. In this way, it is possible to focus on a specific state or a situation and investigate how the other variables in the network react in the presence of the evidence. This process can be repeated for all other variables and also for all states of the variables. As a result of these processes, it is possible to obtain different interpretable networks. In other words, the primary purpose of using the BN is to determine how the states of the other variables are affected when an evidence is set to a specific state of any variable.

3.3. Integration of SEM with BN

A structural equation model begins with a theoretical model that represents causal relationships between variables. Afterward, the researchers design an experiment and collect data to test whether the theoretical model they created is valid. And if so, they want to know what the coefficients are and then interpret these coefficients. The original theoretical model can be slightly adapted based on the results of the SEM assessment in practice since the placement of data in models provides new information. This process includes checking the model fit and parameter estimates as well as making adjustments if the measurement model is not satisfactory in the CFA. When the model is validated, and the SEM gives satisfactory results, the obtained coefficients become the discussion point and direct the arguments for the theoretical model.

In this study, since the variables satisfaction, loyalty, image, trust, and perceived value were not directly observed, a measurement model was constructed by using confirmatory factor model as given in Equation (4). After determination of the observed variables/items of the latent variables/factors through EFA and CFA, the latent variables were made quantitative through their observed variables. The scores were obtained by averages of the observed variables because we further needed categorization of the scores for acquiring predictive ability of BN that different inferences could be made by setting evidence to the states of the nodes in the network with the BN. The advantage of using the BN is that it is possible to instantiate any variable without worrying about the direction of the relationships. Since the data should be in a categorical structure in the BN interpretation, the averages were converted into categories using equal width discretization (Ropero *et al.* 2018). Structure learning algorithms of BN was run to get knowledge extraction on directions of the relationships between the categorized scores, which can be regarded as a white list for BN. The elements of the white list were utilized as prior information in construction of the final model. In this study, the BS algorithm was applied to reach the final model provided by the prior information gained from knowledge extraction from the data. In the BS algorithm, a hill-climbing search is used with random restarts to return the best network, BDe metric is used in order to score candidate networks, and the expectation-maximization algorithm is used to learn the parameters (Cene, Karaman 2015; Cooper, Herskovits 1992; Tonda *et al.* 2013). The BS algorithm may successfully capture the direction of the relationships by itself. However, the number of possible networks increases rapidly as the number of factors increases. For instance, to search possible networks in a 6 factor structure, a total of 3781503 different candidate networks should be searched. In addition, 1138779265 different networks should be searched for a 7 factor structure, so the number of network structures grows super exponentially as the number of factors increases. Therefore, using the knowledge extraction algorithms as prior information not only provides us prior information but also reduces the computational cost. The final model fit were also evaluated from the SEM perspective to assess the relationships from confirmatory point of view. In the last step, BN of the final model were produced to get predictive models by entering evidence on the states of factors. The stages of the approach conducted in the current study were given in Figure 1.

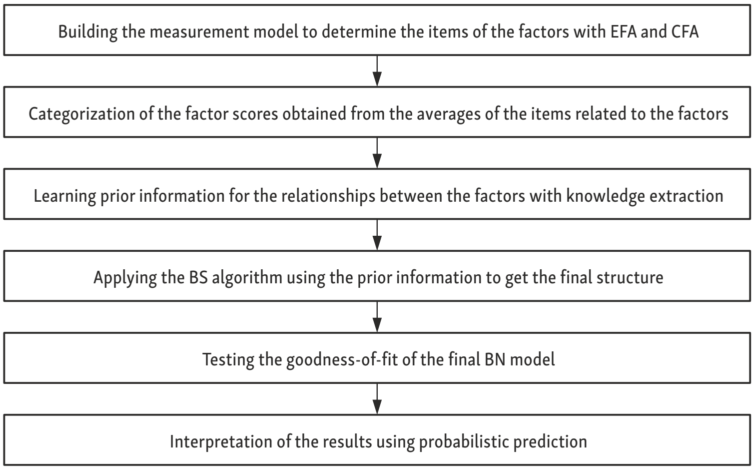

Figure 1. The stages of the study

4. Data and variables

The Turkish State Railways started building high-speed railways in 2003. The 1st section of the line was inaugurated on 13 March 2009 between Ankara and Eskisehir. It is a part of the 533 km Istanbul to Ankara high-speed rail line. The length of the Ankara–Eskisehir railway line is 245 km, and the journey takes about one and a half hours (Akyıldız Alçura *et al.* 2021, 2016). An item pool was generated largely based on the previous literature with the help of expert knowledge. All the questionnaires were responded to by the HSRS passengers on a voluntary basis during the journey on the train. As a result of eliminating the invalid questionnaires, such as the ones in which too many items were skipped, the ones for which the same answers were given, or the useless ones, a total of 900 questionnaires were completed for the subsequent analyses. 10% of the randomly selected respondents were called by phone to verify their participation in the survey. Since the passengers who use HSRS at least several times a week have more experience with the system, their perceptions were analysed in the study. The frequent user sample was consisted of 239 passengers.

The demographic characteristics of these passengers are given in Table 2. As seen from Table 2, 61.1% of the respondents are male. The ages of the users are between 18 and 69. Moreover, 26.4% of the passengers are under the age of 24; 50.6% are between 25…35, 15.5% of the passengers are between 36…45, 7.5% are older than 45. 53.1% of the passengers state their marital status as single. The majority of the passengers have an Associate/BSc degree (50.6%). The distribution of income shows that 42.7% of the passengers' income is between 2501…5000 TRY (≈1001…2150 USD); then comes the income group of less than or equal to 2500 TRY (≈1000 USD) with a percentage of 30.5%, and 11.7% of the passengers state that they have no income. 36% of the passengers use the HSRS every day, and 64% of the passengers use the HSRS several times a week, this means that the passengers included in the study are those who use the HSRS frequently.

In the present study, items scored with 5-point Likert scales ranging from strongly disagree (1) to strongly agree (5) in the questionnaire were considered that they were used to measure the passenger perceptions of image, trust, perceived value, satisfaction, and loyalty. The items were adapted from the existing scales from the literature and/or modified for the transportation sector. Factors with their items, operational definitions, and references were given in Table 3.

Table 2. Demographic characteristics of the respondents

Attribute	Distribution	No	%
Age	≤24	63	26.4
	25…35	121	50.6
	36…45	37	15.5
	46…55	15	6.3
	56…65	2	0.8
	≥65	1	0.4
Gender	male	146	61.1
	female	93	38.9
Education status	primary school	2	0.8
	secondary school	7	2.9
	high school	42	17.6
	associate or BSc	121	50.6
	MSc or PhD	67	28.0
Marital status	single	127	53.1
	married	109	45.6
	divorced/widowed	3	1.3
Income level	no income	28	11.7
	≤2500 TRY (≤1000 USD) per month	73	30.5
	2501…5000TL (1001…2150 USD) per month	102	42.7
	≥5001 TRY (≥2151 USD) per month	36	15.1
Frequency of HSRS usage	everyday	86	36
	several times a week	153	64

Table 3. Operational definitions of factors, and the items in the measurement model

Factor		Item	Adapted from
Image (*impressions and mental pictures of passengers about HSRS*)			
Image	IM1	steady company	Aydin & Özer (2005); Johnson *et al.* (2001); Yilmaz & Ari (2017)
	IM2	strong company	
	IM3	well-established company	
	IM4	preferable company	
	IM5	useful for society	
Trust (*the reliance on the reliability and integrity of HSRS*)			
Trust	TR1	honest company	Akamavi *et al.* (2015); Aydin & Özer (2005); Sayil *et al.* (2019)
	TR2	responsible company	
	TR3	reliable employee	
	TR4	competent employee	
	TR5	honest employee	
	TR6	responsible employee	
Perceived value (*passengers' overall assessment of the net value of the service received*)			
Perceived value	PV1	(the service provided) worth the price paid	Gölbaşı-Şimşek & Noyan (2009); Hellier *et al.* (2003); Zeithaml (1988)
	PV2	(the service provided) worth the effort spent	
	PV3	Convenient the needs	
	PV4	(the comfort provided) worth the effort and money spent	
	PV5	(the safety provided) worth the effort and money spent	
	PV6	(the consistent and planned trip) worth the effort and money spent	
	PV7	met the needs more than expected	
	PV8	(the service provided) worth the effort and money spent in general	
Satisfaction (*overall evaluation of a passenger's usage experiences with HSRS and its service*)			
Satisfaction	SA1	met the expectations	Chou & Kim (2009); Gustafsson & Johnson (2004); Gölbaşı-Şimşek & Noyan Tekeli (2015); Johnson *et al.* (2001); Levesque & McDougall (1996); Yilmaz & Ari (2017)
	SA2	better than the expectations	
	SA3	satisfaction with duration	
	SA4	satisfaction with comfort	
	SA5	satisfaction with punctuality	
	SA6	general satisfaction with HSRS	
Loyalty (*passengers' behavioural and attitudinal willingness to remain with HSRS*)			
Loyalty	LO1	using again	Aydin & Özer (2005); Cronin *et al.* (2000); Gölbaşı-Şimşek & Noyan (2009); Gölbaşı-Şimşek & Noyan Tekeli (2015); Sayil *et al.* (2019)
	LO2	recommendation to others	
	LO3	expression the pleasure	
	LO4	using more in future	

5. Results

In this section, results of EFA, CFA, and reliability assessment are given in Section 5.1. The structure learning and SEM results are provided in Section 5.2. The remainder sub-sections of Section 5 presents the results and interpretations obtained from different BN.

5.1. Measurement model results

The validity and reliability properties for the 5-factor model of the image with the 5 items, trust with the 6 items, perceived value with the 8 items, satisfaction with the 6 items, and loyalty with the 4 items given in Table 3 were assessed. The measurement model of the 5 factors was evaluated on the sample of frequent passengers in 3 steps: EFA, CFA, and reliability assessment. The EFA was performed in SPSS Statistics 25.0 (*https://www.ibm.com/support/pages/downloading-ibm-spss-statistics-25*) with principal axis factoring with *Promax rotation*. KMO and Bartlett's tests were conducted to test the adequacy and the suitability of implementing the factor analysis to the sample. The KMO value was found as 0.948, which is defined as marvellous (Kaiser 1974). According to Bartlett's test (Bartlett 1950), the hypothesis that the correlation matrix is an identity matrix was rejected ($p < 0.01$). At this point, the factor correlations as a result of the *Promax rotation* were analysed. The factor correlation values were higher than the recommended level of 0.32 for oblique rotation (Raykov, Marcoulides 2008). Both the factor pattern matrix and the structure matrix were evaluated. The factor analysis results of the items were found to be appropriate. As a result of the EFA applied to the 29 items given in Table 3, 5 factors were determined. The factors with their items and the *Promax rotation* factor loadings of the items on the relevant factor were shown in Table 4. Most of the factor loadings were all reasonably high (above 0.7). The factors accounted for 72.814% of the total variance. All of the factor loadings of each variable met the minimum 0.30 requirement. Hair *et al.* (2009), ranging from 0.613 to 0.939. Based on the high factor loadings, the 5 factors were accepted for further analyses. The CFA model given in Equation (4) was established for the 5 factors to test the measurement model and to determine if the items were significantly related to the factors. According to the 2-index representation method of Hu and Bentler (1999), the model having χ^2 = 874.84 with 367 d.f. (p < 0.01), normed χ^2 = 2.38, RMSEA = 0.076, NFI = 0.96, NNFI = 0.98, CFI = 0.98, GFI = 0.80, and SRMR = 0.055, and values were found to provide a good fit to the data. The CFA results, including the standardized factor loadings, the standard errors, the t-values, and the R^2 values indicating the item level reliabilities, were given in Table 4. The factor loadings were higher than the offered value of 0.50, and most of them were found to be higher than the ideal value of 0.7 (Hair *et al.* 2009; Hooper *et al.* 2008; Hu, Bentler 1999). Since all the coefficients were found to be significant, the convergent validity of the measurement model was confirmed according to the CFA. Most of the R^2 values were higher than the suggested value of 0.5, having values in the range between 0.34 and 0.88, which shows that more than half of the variance of the items can be explained by the related factors. Harman's single factor test from the EFA perspective and CLF method from the CFA perspective were applied to detect whether common method bias exist in the measurements. The total variance extracted by a single factor was found 49.553%. The square of CLF loading (0.677) was 45.83%. Since the calculated common method variances (49.553% and 45.83%) were less than the threshold of 50%, no considerable common method bias was detected (Fuller *et al.* 2016).

The reliability was assessed using Cronbach's alpha and CR (Cronbach 1951). The Cronbach's alpha coefficients and the CR values given in Table 5 were ranged between 0.88 and 0.94, indicating good reliability considering that 0.70 is the cut-off value for being acceptable (Nunnally 1994). Since all the values were at an acceptable level, with the factor loadings found to be significant and of an acceptable size, the measurement model provided a good fit, and convergent validity was confirmed according to the CFA. A stricter approach for assessing convergent validity is AVE criterion proposed by Fornell & Larcker (1981). The AVE expresses the ratio of the explained variance of the items by the relevant factor to the total variance of these items, and it is recommended that this ratio should be greater than 0.50. So, at least half of the total variance of the items are explained by the relevant factor. The AVE values were calculated using the standardized CFA results of the items for each factor in this study and were presented in Table 5. When Table 5 was examined, it was seen that the AVE values of all factors were larger than 0.50, so convergent validity was shown according to this strict approach. Based on these results, the factors were deemed acceptable.

Discriminant validity examines if the measures in the model are distinct; in other words, whether the measures in the model are highly correlated with each other. In this study, the strategy of Fornell & Larcker (1981) to compare the squared root of the AVE values for each factor was applied to evaluate the discriminant validity between the factors. The diagonal of Table 6 shows the squared root of the AVE values belonging to each factor. In Table 6, below and above the diagonal, the correlation coefficients obtained from CFA and EFA were presented, respectively. The squared root of the AVE value for satisfaction was found to be as 0.75, and this value was not greater than the correlation coefficient between perceived value and satisfaction (0.80), and between satisfaction and loyalty (0.77). However, the differences between the values were relatively small.

At this stage, the χ^2 difference test was applied to evaluate the discriminant validity. Anderson & Gerbing (1988) suggested comparing a constrained model whose parameter estimation is constrained to 1.0 for 2 factors and an unconstrained model for which this parameter was freely estimated. The χ^2 differences were computed for perceived value and satisfaction – $\Delta\chi^2$ = 1177.85 – 874.84 = 303.01, Δd.f. = 368 – 367 = 1; satisfaction and loyalty $\Delta\chi^2$ = 1114.70 – 874.84 = 239.86, Δd.f. = 368 – 367 = 1. The differences in the computed χ^2 values were greater than $\chi^2_{(0.99;\,1)} = 6.635$. Then, the null hypotheses of "the correlation between the given pairs of factors being equal to 1.0" were rejected at .01 level. Thus, discriminant validity was achieved between these pairs. Moreover, CFI, GFI, and NNFI values decreased, and RMSEA values increased in the constrained models compared to the unconstrained model. CFI and NNFI values both for "perfectly correlated perceived value and satisfaction model," and "perfectly correlated satisfaction and loyalty model" decreased from 0.98 to 0.97. GFI values for "perfectly correlated perceived value and satisfaction model" and "perfectly correlated satisfaction and loyalty model" decreased from 0.80 to 0.75 and from 0.80 to 0.76, respectively. RMSEA values for "perfectly correlated perceived value and satisfaction model" and "perfectly correlated satisfaction and loyalty model" increased from 0.076 to 0.096 and 0.076 to 0.092, respectively. Overall, the results revealed that the measures possessed satisfactory fit, reliability, and validity. Thus, the preliminary analyses on the way through the final step were made. The factor scores obtained by averaging the original 5-point Likert scale responses of the variables belonging to the same factor were re-categorized into 5 classes using equal width discretization (Ropero *et al.* 2018). The states of factors were assigned as 1, 2, 3, 4, and 5 according to the average values between 1.00...1.79, between 1.80...2.59, between 2.60...3.39, between 3.40...4.19, and between 4.20...5.00, respectively.

Table 4. Measurement model estimates

Factor		Factor loading (EFA)	Standardized factor loading (CFA)	Standard error	*t*-value	R^2
Image	IM1	0.853	0.87	0.052	16.54*	0.75
	IM2	0.897	0.90	0.047	17.51*	0.81
	IM3	0.765	0.74	0.057	13.12*	0.55
	IM4	0.691	0.69	0.064	11.77*	0.47
	IM5	0.740	0.75	0.054	13.17*	0.56
Trust	TR1	0.764	0.78	0.057	14.27*	0.61
	TR2	0.776	0.79	0.057	14.55*	0.63
	TR3	0.864	0.87	0.049	16.79*	0.76
	TR4	0.904	0.90	0.052	17.76*	0.81
	TR5	0.922	0.90	0.051	17.91*	0.82
	TR6	0.873	0.87	0.054	16.79*	0.76
Perceived value	PV1	0.762	0.75	0.063	13.48*	0.57
	PV2	0.842	0.84	0.054	15.78*	0.70
	PV3	0.749	0.77	0.049	13.82*	0.59
	PV4	0.855	0.83	0.053	15.71*	0.70
	PV5	0.830	0.83	0.052	15.60*	0.69
	PV6	0.866	0.87	0.052	15.60*	0.76
	PV7	0.792	0.79	0.056	16.78*	0.63
	PV8	0.838	0.85	0.051	14.54*	0.73
Satisfaction	SA1	0.787	0.80	0.057	14.47*	0.64
	SA2	0.776	0.78	0.059	14.06*	0.61
	SA3	0.779	0.73	0.063	12.80*	0.54
	SA4	0.709	0.73	0.064	12.46*	0.53
	SA5	0.613	0.58	0.073	9.53*	0.34
	SA6	0.822	0.85	0.050	15.87*	0.72
Loyalty	LO1	0.831	0.80	0.044	14.46*	0.63
	LO2	0.939	0.94	0.048	18.81*	0.88
	LO3	0.725	0.79	0.059	14.22*	0.62
	LO4	0.753	0.76	0.054	13.62*	0.58

Note: * – $p < 0.01$.

Table 5. Cronbach's alpha, CR, AVE values, and eigenvalues

Factor	Cronbach's alpha	CR	AVE	Eigenvalue
Image	0.89	0.89	0.63	1.46
Trust	0.94	0.94	0.73	2.36
Perceived value	0.94	0.94	0.67	4.86
Satisfaction	0.88	0.88	0.56	1.26
Loyalty	0.87	0.89	0.68	1.17

Table 6. Discriminant validity

Factor	Image	Trust	Perceived value	Satisfaction	Loyalty
Image	0.79	0.70	0.63	0.64	0.53
Trust	0.74*	0.85	0.62	0.59	0.51
Perceived value	0.67*	0.65*	0.82	0.73	0.65
Satisfaction	0.68*	0.63*	0.80*	0.75	0.66
Loyalty	0.62*	0.57*	0.73*	0.77*	0.83

Note: * – $p < 0.01$.

5.2. Structure learning results

In order to obtain the prior information, 13 different structures were provided with the help of the structure learning algorithms included in the *bnlearn* package in *R* (Ihaka, Gentleman 1996; *https://www.r-project.org/about.html*). The package includes various algorithms that can give different results (Scutari 2010). The *bnlearn* implements the constraint-based structure learning algorithms (fast incremental association, Grow–Shrink, incremental association Markov blanket, interleaved incremental association, max–min parents and children, Peter–Clark (PC) (Spirtes *et al.* 2001), and semi-interleaved Hiton–PC), the score-based structure learning algorithms (hill-climbing and tabu search), the hybrid structure learning algorithms (general 2-phase restricted maximization, and max–min hill-climbing), and the local discovery algorithms – ARACNE and Chow–Liu (Chow, Liu 1968). If the direct relationship to B from A denoted by A→B exists, it was coded as "1", else "0" for each algorithm. After completing the coding for all relationships, when the total of the A→B is 13, this relationship was considered to be used as the prior information. In this step, there is no need to weight the algorithms, because in this study it was assumed that all algorithms must confirm the existence of a relationship.

With the complete consensus of structure learning algorithms, the prior relationships were obtained as follows:
- trust has an effect on perceived value;
- satisfaction has an effect on loyalty.

The final model was obtained with the help of the BS algorithm in GeNIe software (Druzdzel 1999) as integrating the prior information. The relationships added to the previous ones were determined as follows:
- image has an effect on trust;
- image has an effect on loyalty;
- perceived value has an effect on satisfaction.

Superficially, model fit values were found as RMSEA = 0.08, NFI = 0.96, NNFI = 0.97, CFI = 0.98, SRMR = 0.083. According to the 2-index representation method of Hu & Bentler (1999), the model values were found to provide a good fit to the data. This result coincides with the SEM literature. Table 1 presents the studies that include the latent variables used in this study with their empirically supported relationships between them. As seen from Table 1, the direct links to loyalty from image and satisfaction, to satisfaction from perceived value, to perceived value from trust, and to trust from image are empirically supported.

According to the findings, the final model was given in Figure 2a. In Figure 2a, the states of "I," "II," "III," "IV," and "V" in the network corresponds to the states of "1", "2", "3", "4", and "5" for completely dissatisfied, dissatisfied, neither satisfied nor dissatisfied, satisfied, and completely satisfied, respectively. The percentages inside the boxes reflect the passengers' perceptions involved in the study on the relevant factor. For instance, it is seen from Figure 2a that the image perceptions of 3% of the passengers are "completely dissatisfied," and the image perceptions of 21% of them are "completely satisfied." Likewise, the loyalty perceptions of 49% of the passengers are "completely satisfied," and the loyalty perceptions of 32% of the passengers are "satisfied," so 81% of the passengers involved in this study are loyal to the company.

The classic SEM technique was implemented for the final model to test the validity of the relationships. Path coefficients among latent variables were given on the edges of the network in Figure 2b. As shown in Figure 2b, all of the path coefficients were positive and significant. Superficially, the model fit values were found as χ^2 = 939.94 with 372 d.f. (p < 0.01), normed χ^2 = 2.53, RMSEA = 0.08, NFI = 0.96, NNFI = 0.97, CFI = 0.98, GFI = 0.79, and SRMR = 0.083. According to the 2-index representation method of Hu & Bentler (1999), the final model provides a good fit to the data.

5.3. The effect of image

In order to investigate the effects of a particular factor on the others, setting evidence on its lowest and the highest levels, the changes of the posterior probabilities in the new network were examined. Figure 3a shows the changes to the network, given that image was at its 1st state. After setting an evidence on the 1st state of the image factor,

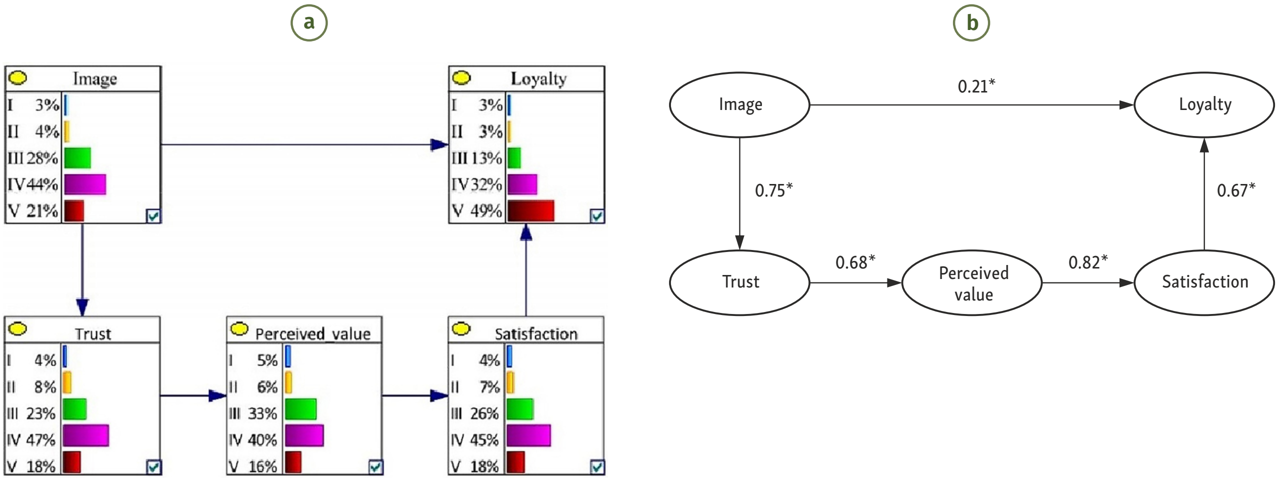

Figure 2. SEM: a – final model; b – results (*note*: **p* < 0.01)

there were sudden changes over the states of the other factors. According to the new model, the most prominent changes appeared on trust. The posterior probability of the lowest state of trust increased from 4 to 74%. It is also seen from Figure 3a that the 1st states of perceived value, satisfaction, and loyalty values were affected similarly by the change of image. The posterior probabilities of the lowest states of perceived value, satisfaction, and loyalty increased from 5 to 50%, from 4 to 30%, and from 3 to 26%, respectively. These values show that the 1st state of image increased the posterior probabilities of the 1st states of the trust, perceived value, satisfaction, and loyalty, especially increased trust the most. Figure 3b shows changes to the network, given that the image factor was at its highest state. It means that the other states of image (1, 2, 3, and 4) and their effects have not been included in the graphic. After setting evidence on the 5th state of the image factor, there were sudden changes over the states of the other factors. According to the new model, the most prominent changes appeared on loyalty and trust. The posterior probabilities of the 5th state of trust, loyalty, perceived value, and satisfaction increased from 18 to 56%, from 49 to 74%, from 16 to 32%, and from 18 to 29%, respectively. The differences between the values were noticeable (between the initial model, Figure 2a), and the changed model, Figure 3b). Based on these values, it could be said that trust in the company and loyalty towards the company were better than the initial model. In other words, one of the shortest ways to increase the trust and the loyalty of the customers is to improve the company's image.

In order to better see the effect of the image on other variables, the 2 figures in Figure 3 can be compared. When passengers with the lowest image perception were set as evidence (Figure 3a), the sum of the 4th and 5th states of loyalty was found to be 41%. However, when the passengers with the highest image perceptions were set to the graphic as evidence, it is seen that the sum of these values was improved to 90%. Another important change was in trust. In Figure 3a, the sum of the 4th and 5th states of trust was found to be 6%, while in Figure 3b this total was rose to 90%. In other words, on the way to increase passenger loyalty, we understand how important the image is because it can increase the percentage of the 4th and 5th states of both trust and loyalty to 90% on its own.

5.4. The effect of trust

If an evidence was set on the 1st state of trust, the most remarkable changes showed up at perceived value (Figure 4a). In this situation, the 1st state of perceived value increased from 5 to 62%. Based on these values, it could be said that the dissatisfaction of trust mostly affected the dissatisfaction of the perceived value. The posterior probabilities of the 1st states of satisfaction, image, and loyalty increased from 4 to 36%, from 3 to 50%, and from 3 to 22%, respectively. Thus, it was seen that the 1st state of trust increased the posterior probabilities of the 1st states of image, perceived value, satisfaction, and loyalty, especially increased perceived value the most. According to Figure 4b, given that trust was at its 5th state, the most remarkable changes assigned to image and perceived value. The posterior probability of the 5th state of image, perceived value, satisfaction, and loyalty increased from 21 to 64%, from 16 to 50%, from 18 to 40%, and from 49 to 70%, respectively. In Figure 4, it is also possible to see the importance of keeping the passengers' trust perceptions at the highest level on the perceived value rather than keeping it at the lowest through the percentage changes. In Figure 4a, the sum of the 4th and the 5th states of perceived value was 4%, while in Figure 4b this total was found to be 82%. Also, in Figure 4a, the sum of the 1st and 2nd states of perceived value was found to be 84%, however in Figure 4b this total was found as 2%. Based on these values, it could be said that the best way to increase the perceived value perceptions is to improve the passengers' trust perceptions. Considering that trust has an indirect effect on loyalty, it is also possible to evaluate the significant changes in loyalty. In Figure 4a, the sum of the 4th and 5th states of loyalty was found to be as 40% while in Figure 4b this total was increased to 90%.

5.5. The effect of perceived value

As seen from Figure 5a, the most noteworthy changes belonged to satisfaction and trust, given that perceived value was at its 1st state. The posterior probability of the lowest state of satisfaction increased from 4 to 55%. Besides, the posterior probabilities of the 1st states of trust, image, and loyalty increased from 4 to 45%, from 3 to 25%, and from 3 to 20%, respectively. According to these values, the 1st state of perceived value increased the posterior probabilities of the lowest states of image, trust, satisfaction, and loyalty, especially increased the satisfaction factor the most. Figure 5b shows that the most noteworthy changes were on the satisfaction factor, given that perceived value was at its 5th state. The posterior probability of the 5th state of satisfaction, image, trust, and loyalty factors increased from 18 to 70%, from 21 to 42%, from 18 to 57%, and from 49 to 73%, respectively. These values showed that the 5th state of perceived value increased the posterior probabilities of the highest states of image, trust, satisfaction, and loyalty, especially increased the satisfaction factor the most. Consequently, in order to make the passengers' satisfaction better, the perceived value perceptions of the passengers are needed to be increased.

In Figure 5, it is also possible to see the importance of keeping the passengers' perceived value perceptions at the highest level on the satisfaction rather than keeping it at the lowest through the percentage changes. In Figure 5a, the sum of the 4th and the 5th states of satisfaction was 11%, while in Figure 5b this total was found to be 93%. Also in Figure 5a, the sum of the 1st and 2nd states of satisfaction was 64%, however in Figure 5b this total was found as 2%. Based on these values, it could be said that the best way to increase the satisfaction perceptions is to improve the passengers' perceived value perceptions.

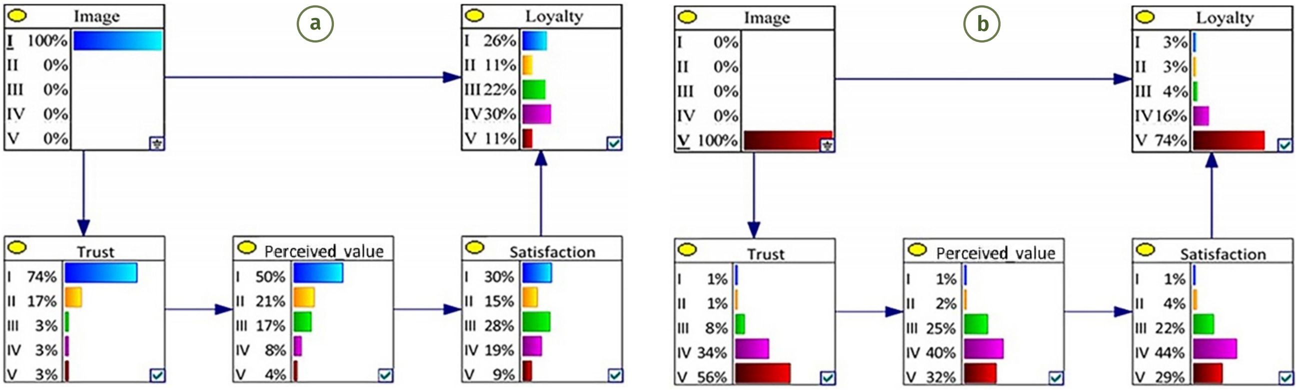

Figure 3. Changes in the network after setting an evidence on the: (a) – lowest state of the image; (b) – highest state of the image

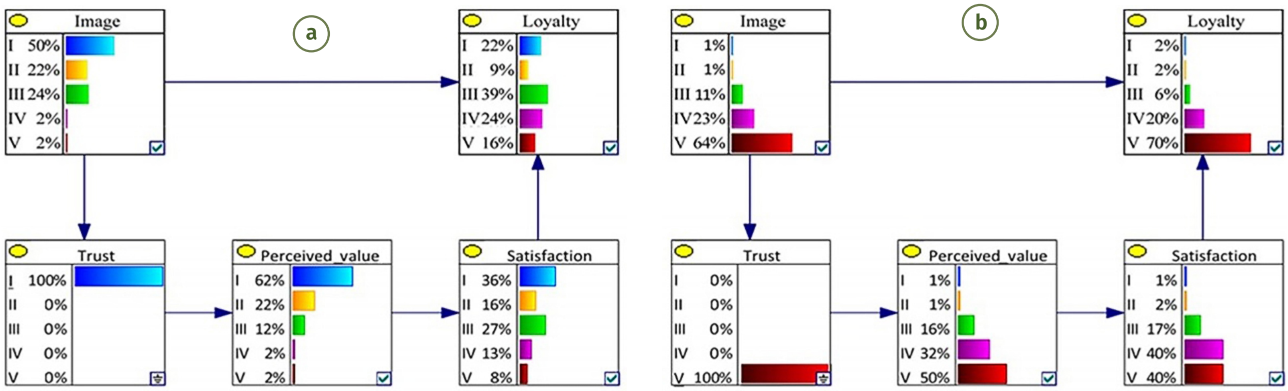

Figure 4. Changes in the network after setting an evidence on the: (a) – lowest state of the trust; (b) – highest state of the trust

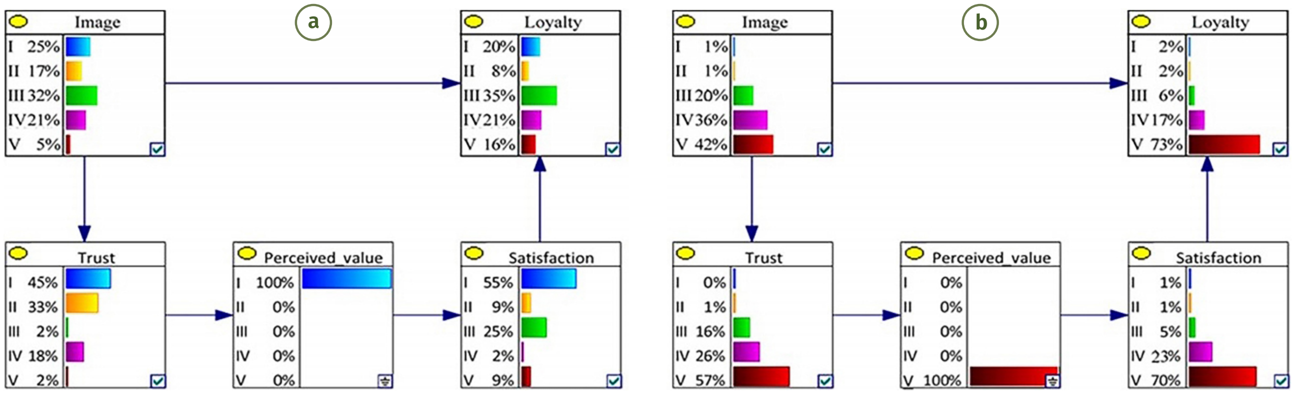

Figure 5. Changes in the network after setting an evidence on the: (a) – lowest state of the perceived value; (b) – highest state of the perceived value

Considering that perceived value has an indirect effect on loyalty, it is also possible to evaluate the significant changes in loyalty. In Figure 5a, the sum of the 4th and 5th states of loyalty was found to be as 37%, while in Figure 5b this total was increased to 90%.

5.6. The effect of satisfaction

Figure 6a shows that the most noticeable changes accompanied with perceived value given that satisfaction was at its 1st state. The posterior probabilities of the 1st states of image, trust, perceived value, and loyalty increased from 3% to 19%, from 4 to 35%, from 5 to 72%, and from 3 to 27%, respectively. These values show that the lowest state of satisfaction increased the posterior probabilities of the lowest states of image, trust, satisfaction, and loyalty, especially increased the posterior probability of perceived value the most. As seen from Figure 6b given that satisfaction was at its 5th state, the most noticeable changes accompanied with the perceived value and loyalty. The posterior probabilities of the 5th states of perceived value, loyalty, image, and trust increased from 16 to 62%, from 49 to 78%, from 21 to 33%, and from 18 to 40%, respectively. According to these values and the learned relationship, it was supported that passengers' satisfaction perceptions are needed to be improved to increase the passengers' loyalty.

In Figure 6, the 2 figures can be compared to see the magnitude of the effect of satisfaction on loyalty. When an evidence was set on the 1st state of satisfaction (Figure 6a), the sum of the 4th and 5th states of the loyalty was found to be 18%. However, when an evidence was set on the 5th state of satisfaction (Figure 6b), the sum of the 4th and 5th states of loyalty was found to be 90%. It is observed that keeping the passengers' satisfaction perceptions at the lowest level and keeping them at the highest level creates a significant change in the passengers' loyalty perception. Thanks to BN, we can see the magnitude of this change over the existing data set. This difference was found to be approximately 72% and corresponds to almost 3-quarters of all passengers.

5.7. Different scenarios

Only one piece of evidence was set for each BN in the previous figures, instead of this, there will be evidence for more than one latent variable at a time in each BN. In Figure 7a it is seen that how setting evidence on the 1st states of all variables except loyalty influences loyalty. This network may answer the question: "How do passengers who are fully dissatisfied about image, trust, perceived value, and satisfaction shape the loyalty factor towards the company?". Although the dissatisfaction (1st, lowest) evidence was set to the latent variables, it was determined that the posterior probability of the 4th state and the 5th state of the loyalty were both found to be 5%. In addition, the posterior probability of the 3rd state of loyalty was found to be 30%. It means that 30% of the passengers were found to be undecided about whether they are loyal to the company or not. The posterior probability of the 1st state of the loyalty variable was 55%, so 55% of the dissatisfied passengers are also not loyal to the company.

In Figure 7b, it is seen how entering evidence on the 3rd states of image, trust, perceived value, and satisfaction influence loyalty. This network may answer the question: "How do the passengers who are stated to be "neither satisfied nor dissatisfied" with image, trust, perceived value, and satisfaction shape loyalty factor towards the company?". According to the network, the 5th and 4th states of loyalty were found to be 16 and 49%, respectively. Based on these values, 65% of the passengers undecided about image, trust, perceived value, and satisfaction were found to be loyal to the company. In comparison, only a 3rd (33%) of these were found to be unsure about loyalty to the company. Approximately 2% of passengers undecided about image, trust, perceived value, and satisfaction were found not to be loyal to the company. Namely, although the passengers are undecided about whether they are satisfied with image, trust, perceived value, and satisfaction or not, most of them are loyal to the company.

In Figure 7c, it is seen how entering evidence on the 5th states of image, trust, perceived value, and satisfaction influence loyalty. This network may answer the question: "How do the passengers who are stated to be completely satisfied with image, trust, perceived value, and satisfaction shape the variable of loyalty towards the company?". According to the network, the 4th and 5th states of loyalty were found to be 93% and 4%, respectively. Based on these values, 97% of the passengers completely satisfied with image, trust, perceived value, and satisfaction were found to be loyal to the company. The 1st and 2nd states of the loyalty were found to be both 1%. Therefore, only about 2% of the passengers stated that they were not loyal to the company. This number is considered to be quite negligible. In other words, almost all of the passengers stated that they are loyal to the company. In Figure 7, it can be seen how loyalty changes when entering evidence on more than one variable simultaneously. From this perspective, it is clear that as passengers' perceptions on the image, trust, perceived value, and satisfaction were fulfilled as a whole, loyalty increases dramatically.

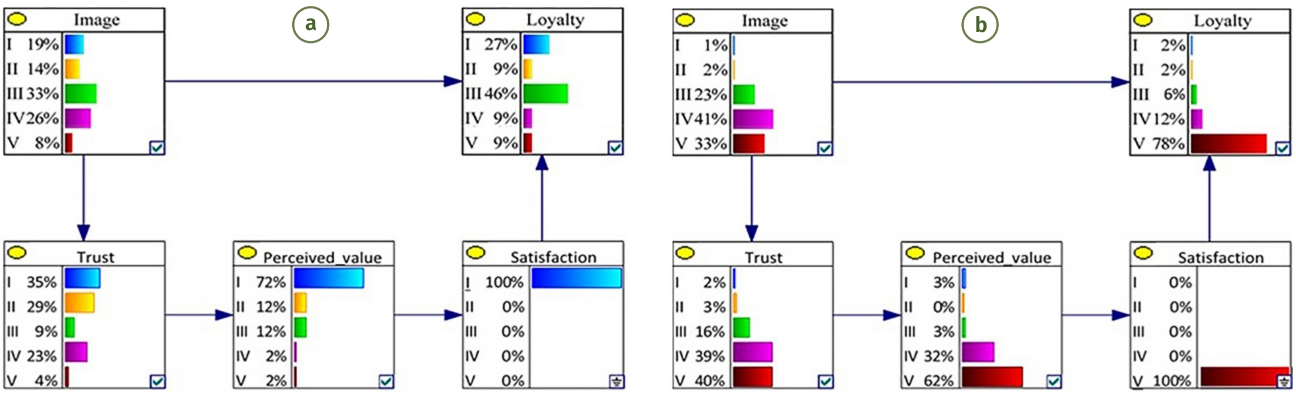

Figure 6. Changes in the network after setting an evidence on the:
(a) – lowest state of the satisfaction; (b) – highest state (b) of the satisfaction

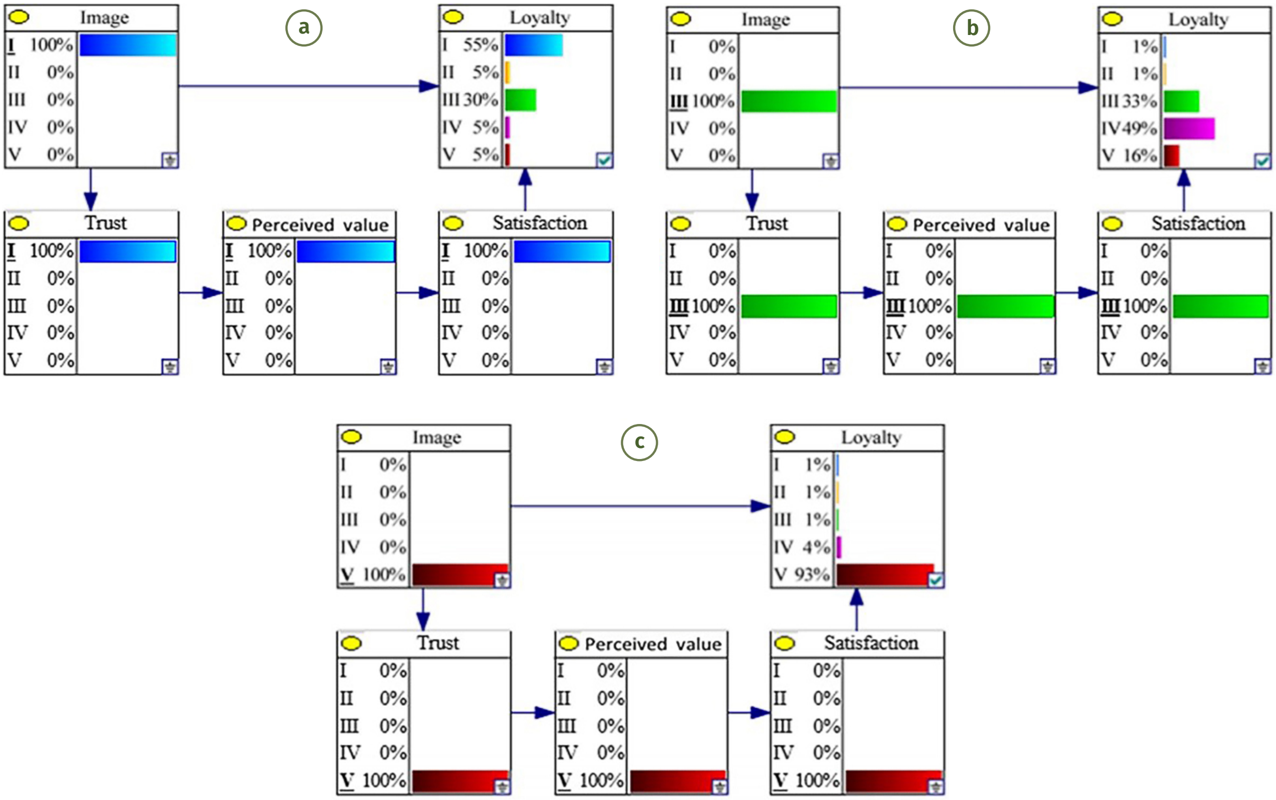

Figure 7. Changes in the network after setting evidence on the: (a) – 1st states of image, trust, perceived value, and satisfaction; (b) – 3rd states of image, trust, perceived value, and satisfaction; (c) – 5th states of image, trust, perceived value, and satisfaction

6. Conclusions and managerial implications

In the present study, it is aimed to conduct a hybrid approach combining SEM with BN to investigate the relationships among the HSRS passengers' satisfaction, loyalty, image, trust, and perceived value. After building the measurement model as the classical SEM techniques, the prior information for the relationships among the factors was learned with the knowledge extraction from the data technique. In order to reach the final model provided by the prior information, the BS algorithm, which is one of the search and score algorithms implemented in the GeNIe, was used. The direct links to loyalty from image and satisfaction, to satisfaction from perceived value, to perceived value from trust, and to trust from image were empirically supported. These relationships are in line with those of previous studies in the literature. In order to investigate whether the approach was successful or not, the validity of the final model was empirically checked as made in the classical SEM. According to the SEM goodness-of-fit indices, the model values were found to provide a good fit to the data.

After getting the final model, a piece of evidence was set on a specific state of a particular perception variable. In this way, it was possible to evaluate how other variables were affected by it. In this regard, this study contributes to the literature by taking the classical SEM method to the next level by examining how the variables affect each other in a percentage way as a result of different scenarios. Percentage changes of the states of the variables were evaluated in each different scenario. In this way, it can be determined what kind of action can be taken to increase the loyalty perceptions of the HSRS passengers.

In the worst-case scenario, it was found that 10% of the passengers were loyal, while in the best-case scenario, 97% of the passengers were determined to be loyal to the company. This model approach makes it possible to find answers to many questions for each scenario. At this point, the most remarkable findings can be evaluated. While the total percentage of the 4th and 5th states of loyalty (satisfied and completely satisfied passengers) was found to be 81% in the initial model, it was determined that this total can be increased to a maximum of 90% when evidence was set separately to the 5th states of the image, trust, perceived value, and satisfaction. Moreover, the total of the loyal passengers was found to be 97% when the 5th states of all the other factors were set as 100%.

According to the findings, it is recommended that HSRS providers should work on improving the image and satisfaction perceptions of passengers to increase the loyalty perceptions. When an evidence was set on the 5th state of both the image and satisfaction, it was detected that the sum of the 4th and 5th states of loyalty was found to be 97%. It is also recommended for the managers to develop a web application to collect data about passengers' loyalty perceptions and other factors that are proved to be effective on loyalty periodically. Through a web application to be created, the percentage changes in the passengers' loyalty perceptions together with the feedback received from the passengers can be followed up-to-date. For this process, it is sufficient for HSRS providers to ask one of the validated items for each factor specified in the measurement model. It is thought that this web application will contribute to the image of the company if it provides easy and simple access to the information related to the service offered. Another important practical implication is that the personnel providing the service should be competent and willing to meet the needs of the passengers and solve the problems effectively and quickly. This will reinforce the trust in the company and lead passengers to have a positive value perception and satisfaction with the service they receive. It is important for sustainability to follow up the model up-to-date and take action immediately to improve the loyalty perceptions of the passengers.

This study provides the following insight for future research: utilizing the flexi structure of BN, comparisons of models and networks can be made according to the attributes of passenger and transportation such as social or demographical characteristics of passengers, type of transportation, purpose of transportation, and duration of transportation.

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Author contributions

Tugay Karadağ and *Gülhayat Gölbaşi Şimşek* conceived the study and were responsible for the design and development of the data analysis.

Gülhayat Gölbaşi Şimşek and *Güzin Akyildiz Alçura* supervised the work.

Tugay Karadağ and *Gülhayat Gölbaşi Şimşek* wrote the original draft, while *Gülhayat Gölbaşi Şimşek* and *Güzin Akyildiz Alçura* reviewed and edited the manuscript.

All authors discussed the results and commented on the manuscript.

Disclosure statement

The authors declare that they have no competing financial, professional, or personal interests from other parties.

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