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YILDIZ TECHNICAL UNIVERSITY

GRADUATE SCHOOL OF SCIENCE AND ENGINEERING

PROBABILISTIC STRUCTURAL EQUATION MODELING APPROACH TO INVESTIGATE THE RELATIONSHIPS BETWEEN IMAGE, TRUST, PERCEIVED VALUE, SATISFACTION, AND LOYALTY

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MASTER OF SCIENCE THESIS

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A thesis submitted by Tugay KARADAĞ in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE** is approved by the committee on 04.06.2021 in Department of Statistics, Statistics Program.

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Tugay KARADAĞ

Signature

Dedicated to my family

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TABLE OF CONTENTS

LIST OF SYMBOLS vii
LIST OF ABBREVIATIONS viii
LIST OF FIGURES x
LIST OF TABLES xi
ABSTRACT xii
ÖZET xiv
1 INTRODUCTION 1
1.1 Literature Review 1
1.2 Objective of the Thesis 3
1.3 Hypothesis 3
2 BACKGROUND 4
2.1 Introduction 4
2.2 Definition and the Use of the Factors 6
2.2.1 Perceived Value 6
2.2.2 Customer Loyalty 7
2.2.3 Image 7
2.2.4 Trust 8
2.2.5 Satisfaction 9
3 METHODS 10
3.1 Structural Equation Modeling 10
3.1.1 Factor Analysis 13
3.1.2 Path Analysis 13
3.1.3 Assessing the Model Fit in SEM 14
3.2 Bayesian Networks 17
3.2.1 Definitions 17
3.2.2 Introduction to Bayesian Networks 18
3.2.3 What-if Analysis: Interpretation in Bayesian Networks 20
3.2.4 D-Separation 23
3.2.5 Learning Process in Bayesian Networks 23
3.3 Probabilistic Structural Equation Modeling 24

4 DATA AND VARIABLES 27
5 RESULTS AND DISCUSSION 30
5.1 Measurement Model Results 30
5.2 Structure Learning Algorithms Results 33
5.3 Semi-PSEM Results 34
5.3.1 The Effect of the Image 36
5.3.2 The Effect of the Trust 38
5.3.3 The Effect of the Perceived Value 40
5.3.4 The Effect of the Satisfaction 41
5.3.5 The Effect of the Loyalty 43
5.3.6 Different Scenarios 45
5.4 Conclusions and Recommendations 48
REFERENCES 52
A THE RELATIONSHIPS BETWEEN IMAGE, SATISFACTION, TRUST, VALUE, AND LOYALTY ACCORDING TO THE PREVIOUS SEM STUDIES 66
PUBLICATIONS FROM THE THESIS 69

LIST OF SYMBOLS

β	(Beta) Structural coefficients from any η to another η
CO/CO2	Carbon monoxide/carbon dioxide
χ2	Chi-square
df	Degrees of freedom
δ	(Delta) Measurement errors in observed exogenous variable
ε	(Epsilon) Measurement errors in observed endogenous variable
η	(Eta) Latent endogenous variable
γ	(Gamma) Structural coefficients from any ξ to any η
ξ	(Ksi) Latent exogenous variable
λ	(Lambda) Factor loading
∏	Pi
ζ	(Zeta) Structural disturbances

LIST OF ABBREVIATIONS

AGFI	Adjusted Goodness-of-Fit Index
AIC	Akaike Information Criterion
AR	Aracne Algorithm
AVE	Average Variance Extracted
BDe	Bayesian Dirichlet Score Metric
BN	Bayesian Network
BS	Bayesian Search
CAIC	Consistent Akaike Information Criterion
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CH	Chow-Liu
CPT	Conditional Probability Table
CR	Composite Reliability
DAG	Directed Acyclic Graph
EBN	Exploratory Bayesian Network
ECVI	Expected Cross-validation Index
EFA	Exploratory Factor Analysis
EM	Expectation-Maximization Algorithm
F.IA	Fast Incremental Association,
GeNIe	Graphical Network Interface
GFI	Goodness-of-fit index
GS	Grow-Shrink
HC	Hill Climbing
HSRS	High-Speed Railway Systems
I.IA	Interleaved Incremental Association
IA	Incremental Association Markov Blanket
IM	Image
KMO	Kaiser-Mayer-Olkin
LO	Loyalty
LRT	Light Rail Transit

MH	Max-Min Hill Climbing
MP	Max-Min Parents & Children
NFI	Normed Fit Index
NNFI	Non-Normed Fit Index
PGFI	Parsimony Goodness-of-Fit Index
PhD	Doctor of Philosophy
PNFI	Parsimony Normed Fit Index
PSEM	Probabilistic Structural Equation Modeling
RMR	Root Mean Square Residual
RMSEA	Root Mean Square Error of Approximation
RNI	Relative Noncentrality Index
RS	General 2-Phase Restricted Maximization
SA	Satisfaction
SCI	Science Citation Index
SCI-E	Science Citation Index-Expanded
SEM	Structural Equation Modeling
SH	Semi-Interleaved Hiton-PC
SPSS	Statistical Package for the Social Sciences
SQ	Service Quality
SRMR	Standardized Root Mean Square Residual
SSCI	Social Sciences Citation Index
TA	Tabu Search
TLI	Tucker-Lewis index
TOT	Total
TR	Trust
VA	Perceived Value

LIST OF FIGURES

Figure 3.1 Example of exogenous (a) and endogenous (b) measurement model 10
Figure 3.2 An example of a structural model 11
Figure 3.3 An example of a path diagram 14
Figure 3.4 An example of a directed acyclic graph 18
Figure 3.5 Structure of node chains: chain (a), fork (b), v-structure (c) 20
Figure 3.6 An example of evidence setting in Bayesian network 21
Figure 3.7 Probabilistic structural equation modeling processes (Yoo, 2018) ... 25
Figure 3.8 The stages of the study 26
Figure 5.1 Clustering of variables using greedy thick thinning algorithm 31
Figure 5.2 PSEM Results 35
Figure 5.3 Changes in the network after setting an evidence on the lowest state (a) and the highest state (b) of the image 38
Figure 5.4 Changes in the network after setting an evidence on the lowest state (a) and the highest state (b) of the trust 39
Figure 5.5 Changes in the network after setting an evidence on the lowest state (a) and the highest state (b) of the perceived value 41
Figure 5.6 Changes in the network after setting an evidence on the lowest state (a) and the highest state (b) of the satisfaction 43
Figure 5.7 Changes in the network after setting an evidence on the lowest state (a) and the highest state (b) of the loyalty 45
Figure 5.8 Changes in the network after setting evidence on the lowest states of image, trust, perceived value, and satisfaction 46
Figure 5.9 Changes in the network after setting evidence on the third states of image, trust, perceived value, and satisfaction 47
Figure 5.10 Changes in the network after setting evidence on the highest states of image, trust, perceived value, and satisfaction 48

LIST OF TABLES

Table 3.1 Definitions of the symbols in SEM..... 11

Table 3.2 Model goodness-of-fit indices and their admissibility limits 17

Table 4.1 Demographic characteristics of the respondents..... 28

Table 4.2 Factors with items, factor loadings (EFA), and CFA estimates of the measurement model 29

Table 5.1 Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) values 32

Table 5.2 The results of the "knowledge extraction from the data" step 33

ABSTRACT

Probabilistic Structural Equation Modeling Approach to Investigate the Relationships Between Image, Trust, Perceived Value, Satisfaction, and Loyalty

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Master of Science Thesis

Advisor: Prof. Dr. Gülhayat GÖLBAŞI ŞİMŞEK

Structural equation modeling (SEM) is used for modeling customer perceptions, especially in the transportation community. A strong theoretical background and empirical support are necessary for each relationship between the factors. Nevertheless, some obscure issues may exist in model building, like the uncertainty of the direction of the relationship between any two variables or the insufficiency of expert knowledge on the research subject. Even if there is a theory-driven model, the researcher would like to see the reflection of the model in the data; otherwise, s/he would like help from the data. At this point, the probabilistic SEM (PSEM) methodology, which is a hybrid approach integrating SEM with Bayesian network (BN), may help the researchers to find out the directions of the relationships between factors. By having a BN to work with, SEM researchers may also have additional interpretation opportunities, with the help of the dynamic side of the approach. The relationships between the factors may be learned through knowledge extraction algorithms stated in this thesis, in place of the

causal link theory or the previous studies in the literature. In this thesis, semi-PSEM, which is a particular case of PSEM, was implemented to model the relationships between satisfaction, loyalty, image, trust, and perceived value, which are passenger perceptions related to the service provided in the high-speed rail system (HSRS) operating between Ankara and Eskisehir. As a result, it was found that image has a positive effect on trust and loyalty, trust has a positive effect on perceived value, perceived value has a positive effect on satisfaction, and satisfaction has a positive effect on loyalty. The validity of the relationships was empirically supported by the goodness-of-fit measures of SEM. The dynamic probabilistic predictive ability of BN was used to investigate the effect of the perceptions of HSRS passengers.

Keywords: Bayesian networks, loyalty, probabilistic structural equation modeling, satisfaction, transportation

ÖZET

İmaj, Güven, Algılanan Değer, Memnuniyet ve Sadakat Arasındaki İlişkileri Araştırmada Olasılıksal Yapısal Eşitlik Modellemesi Yaklaşımı

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Yapısal eşitlik modellemesi (YEM), özellikle ulaşım sektöründe müşteri algılarını modellemek için kullanılır. Müşteri algıları arasındaki her ilişki için güçlü bir teorik arka plan ve ampirik destek gereklidir. Bununla birlikte, herhangi iki değişken arasındaki ilişkinin yönünün belirsizliği veya araştırma konusu hakkında uzman bilgisinin yetersizliği gibi model oluşturmada bazı belirsiz konuların varlığından söz edilebilir. Eğer bir model teorik odaklı olsa bile, araştırmacı modelin verilerdeki yansımasını görmek ister; aksi takdirde verilerden yardım ister. Bu noktada, YEM'i Bayes ağı ile bütünleştiren hibrit bir yaklaşım olan olasılıksal SEM (PSEM) metodolojisi, faktörler arasındaki ilişkilerin yönlerini bulmada araştırmacılara yardımcı olabilir. SEM araştırmacıları Bayes ağlarını kullanarak yaklaşımın dinamik yönü sayesinde ek yorumlama imkanına sahip olabilirler. Faktörler arasındaki ilişkiler klasik yöntemler yerine bu tezde bahsedilen bilgi çıkarma algoritmaları ile de öğrenilebilir. Bu çalışmada, Ankara-Eskişehir illeri arasında faaliyet gösteren yüksek hızlı tren sisteminde verilen

hizmetle ilgili yolcuların memnuniyet, sadakat, imaj, güven ve algılanan değer algıları arasındaki ilişkileri modellemek için yarı olasılıksal yapısal eşitlik modellemesi yaklaşımı uygulanmıştır. Sonuç olarak, imajın güven ve sadakat üzerinde, güvenin algılanan değer üzerinde, algılanan değerin memnuniyet üzerinde, memnuniyetin de sadakat üzerinde olumlu etkisi olduğu tespit edilmiştir. İlişkilerin geçerliliği, yapısal eşitlik modellemesi uyum iyiliği ölçümleriyle ampirik olarak da desteklenmiştir. Bayes ağları yardımıyla yüksek hızlı tren yolcularının algılarının etkileri farklı senaryolarda değerlendirmiştir.

Anahtar Kelimeler: Bayes ağları, sadakat, olasılıksal yapısal eşitlik modellemesi, memnuniyet, ulaşım

1
INTRODUCTION

1.1 Literature Review

SEM has gained the most attention in the context of causal models with factors. However, there have been limited studies where SEM and BN are combined. When the studies using SEM and BN together were searched in Web of Science, 18 of them linked SEM with BN out of 54. None of those studies has evaluated the probabilistic side of this approach, setting evidence on the states of the factors. This hybrid technique has been used in different ways. Xu et al. (2016) proposed an approach that incorporates both BN and SEM as SEM was applied to enhance the model structure for BN. They demonstrated that using a hybrid strategy minimizes the demand for expert knowledge. They also stated that using this methodology allows BN models to have more acceptable structures, which improves the model's accuracy and reliability. Li et al. (2018) developed an integrated method by combining SEM and BN. They developed SEM-BN models to explore the complex relationships among the factors. Tao and Fan (2017) proposed a model for which the empirical analysis was implemented in three steps that combine confirmatory factor analysis, SEM, and BN. Duarte et al. (2015) proposed a method that combines the effectiveness of existing BN learning algorithms with the statistical rigor of SEM. Hsu et al. (2013) proposed an integrated BN approach that uses SEM for discovering the knowledge of the belief or causal linkages, which then used as the BN model to predict the e-learning attendance level. In order to come through the difficulty of creating a BN structure while extracting information from the data, SEM was used to help BN in finding a suitable network structure for estimation. According to the results, when compared to other techniques, the SEM-BN approach outperformed back-propagation neural networks and classification and regression trees. Yoo and Oh (2013) applied a method using BN and SEM. In their study, it was shown that

combining BN and SEM makes it possible to perform a data-driven prediction model with factors. Díez-Mesa et al. (2018) applied a two-step methodology that used BN and SEM approaches to model service quality (SQ) in the Seville Metropolitan Light Rail Transit (LRT) Service (Spain). The proposed approach was used in the study to extract and confirm the probable linkages between LRT service factors and how they relate to the overall perception of SQ straight from the data without preceding knowledge. SEM was used to assess the model and the linkages between the factors after automated BN learning from the data to find the relationships between SQ dimensions describing the service. Model fit parameters utilized in SEM supported and validated the designed SQ model and its consistency with the real-life scenario. Addae et al. (2019) applied partial least squares SEM to the cybersecurity data regarding users' attitudes towards digital security and searched how it affects their adoption and use of technological security controls. They then used the BN model to combine behavioral factors with simulated sensory input and logs from a web browsing session, as well as other empirical data, to provide personalized adaptive cybersecurity decision making. Duering et al. (2013) applied SEM and BN analyses together to determine a strategic brain network for processing speed deficits in patients with cerebral small vessel disease. For analysing accident risk in complex blasting operations, Gerassis et al. (2019) applied probabilistic SEM by using BN. Gupta and Kim (2008) proposed linking BN to SEM approach and applied this approach to decision support for customer retention in a virtual community. Hsu et al. (2009) combined the linear structural relation model and BN for predicting loyalty of tourists in an area in Taiwan. Jakobowicz and Derquenne (2007) presented a two-step model construction strategy; the first one is based on BN structure learning for building the measurement model, and the second one is to build the structural model. S. R. Wu et al. (2015) applied SEM and BN in their study to identify unobservable impact pathways of the type II model quantitatively and to develop a hybrid model for the social life cycle impact assessment. Gudimov et al. (2012), Jiang and Mahadevan (2009), Mengoli et al. (2016), Töpner et al.

(2017), and Zheng and Pavlou (2010) have also applied SEM with BN in a similar manner.

1.2 Objective of the Thesis

The objective of the thesis is to investigate the relationships between satisfaction, loyalty, image, trust, and perceived value, which are passenger perceptions related to the service provided in HSRS operating between Ankara and Eskisehir. For this purpose, the relationships between the perception variables were learned through neither the causal link theory nor the previous studies in the literature but the knowledge extraction algorithms. The literature was used only to build a measurement model to score the perception variables. This approach is called Semi-PSEM, which is a special case of PSEM. After that, the consistency of the relationships with the literature was also supported.

1.3 Hypothesis

Research question 1. A priori knowledge over the direction of the relationships among the factors can be learned with the help of the data-driven approach. Is this approach useful when building an ideal model?

Research question 2. Can combining SEM with BN provide a more comprehensive perspective than the traditional way of interpretation when exploring ways to increase behavioral intentions?

Research question 3. What are the directions of the relationships among the perception variables?

Hypothesis 1. Image has a positive effect on trust.

Hypothesis 2. Image has a positive effect on loyalty.

Hypothesis 3. Trust has a positive effect on perceived value.

Hypothesis 4. Perceived value has a positive effect on satisfaction.

Hypothesis 5. Satisfaction has a positive effect on loyalty.

2
BACKGROUND

2.1 Introduction

High-speed railway systems (HSRS) improve rail service quality while also increasing customer satisfaction. They also contribute to the development of socioeconomically balanced societies (He et al., 2016). In order to be classified as a high-speed train in commercial service, it must travel at least 250 kilometers per hour. HSRS is currently used in a number of European countries, including Italy, Germany, and Spain, as well as Japan, China, and South Korea. In 2003, the Turkish State Railways began construction of high-speed railways. The first section of the line between Ankara and Eskisehir was inaugurated on March 13, 2009. It is part of a 533-kilometer high-speed rail line connecting Istanbul and Ankara. The Ankara-Eskisehir railway line is 245 kilometers long and takes about one and a half hours to travel (Akyildiz Alcura et al., 2016).

Compared with other transportation options, a high-speed rail system has the following advantages of lower energy consumption (roughly 20% of that of a car), lower land acquisition costs (roughly 20% of equivalent highway needs), lower environmental impact (roughly.625 percent of automobile CO/CO2 emissions), and higher energy performance (per seat/km, energy requirements are roughly 20% of those of a car) (Chou & Kim, 2009).

It is inevitable that HSRS competes with other transportation systems such as highway and airline to attract customers (Akyildiz Alcura et al., 2021). Therefore, HSRS should have an advantage over other transportation systems, so that passengers may prefer HSRS over other transportation systems. Identifying the factors affecting customer loyalty will give managers the opportunity to optimize limited resource use, keep loyal customers in the system, and also attract new customers. Sirohi et al. (1998) stated that understanding the loyalty intentions

and determinants of existing customers is an essential basis to identify the best retailer activities.

After investigating the relevant literature on modeling customer perceptions, it was found that SEM was used predominantly. One of the most crucial stages of SEM is to determine the hypotheses for the causal connections of latent variables, even if a strong measurement model with appropriate psychometric properties is provided. The consequences of misidentifying a model in SEM may lead to misleading inference for the entire model with direct and indirect relationships. Empirical supports are required for each relationship in the model, as well as a persuasive theoretical background. However, some obscure issues may arise in modeling. 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 and Phou (2013), and Jang et al. (2013) indicated that satisfaction has a positive effect on trust.
- Chi and Qu (2008), Ryu et al. (2012), Brown and Mazzarol (2009), and Alves and 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 and 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 researcher would like to see its reflection in the data, or else s/he would like to get help from the data. At this point, the PSEM methodology, which is a hybrid approach integrating SEM with BN, may help the researchers in order to find out the directions of the relationships between factors. It also can make interpretations of the model useful for a particular purpose.

2.2 Definition and the Use of the Factors

In this section, after giving brief definitions of factors, the extensive literature on them is emphasized in order to provide an insight that they are worth making an alternative investigation.

2.2.1 Perceived Value

Perceived value is considered an interdisciplinary concept linked with business, economics, psychology, and sociology (Ozturk, 2016). According to Zeithaml (1988),

- Value means low price,
- Value is whatsoever anyone wants to see in a product,
- Value is the quality anyone receives for the price s/he pays,
- Value means what anyone gets in return for what s/he gives.

These four consumer value expressions can be briefly described as follows: perceived value (or value) is the customers' overall assessment of the net value of the service received, based on what the customer has received from benefits provided by the service and what has been given to the customer based on cost or sacrifice in obtaining and using the service (Hellier et al., 2003). In other words, perceived value represents the inconsistency between perceived benefits and perceived cost (Lai & Chen, 2011; Lee & Cunningham, 2001; Sumaedi et al., 2012). Concerning its total cost, perceived value is customers' perceptions of the total service value (Jomnonkwao et al., 2015). According to the literature, it could be said that perceived value is described as an antecedent to satisfaction and behavioral intentions in model building (Wen et al., 2005). It has been determined that there have been 635 studies about perceived value and SEM in Web of Science up to now (the query is: TOPIC: (structural+equation +model*) AND TOPIC: (perceived+value) Timespan: All years. Indexes: SCI-EXPANDED, SSCI.). The studies of Kuo et al. (2009), Lai and Chen (2011), Lee et al. (2007), Sirohi et al. (1998), and Ryu et al. (2012) have been the most noteworthy studies among them.

2.2.2 Customer Loyalty

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 loyalty have a significant advantage over their competitors (Cati & Kocoglu, 2008). Loyalty is a commitment to continually re-purchase or retain a preferred product/service in the future. Therefore, despite marketing efforts that may result in situational effects and switching behavior, it causes repetitive purchases with the same brand or set of brands (Oliver, 1999). Loyalty means a non-random tendency of many consumers to buy products from the same company over time and associate good images with that company's products (Maignan et al., 1999). According to the marketing literature, it has been shown that there are two ways to define customer loyalty. Attitudinal loyalty is the first of these and the second is behavioral loyalty. Different feelings, which define an individual's loyalty degree, enable an individual to be generally bound to a product, service, or organization in attitudinal loyalty. Continuing purchasing services from the same supplier, increasing the scale or scope of a relationship, or recommending the supplier to someone can be given as an example of behavioral loyalty. (Fournier, 1994; Hallowell, 1996; Jacoby & Kyner, 1973; Yi, 1990). There are 1652 articles about SEM and loyalty in Web of Sciences up to now. Among others, the most prominent articles related to the loyalty are Bart et al. (2005), Flavián et al. (2006), Maignan et al. (1999), Salanova et al. (2005), and Yoon and Uysal (2005).

2.2.3 Image

The concept of the impressions and the mental pictures of consumers about the brands is defined as image (Finn, 1961). Generally, a service company cannot hide behind brand names. In most cases, throughout the buyer-seller interaction, consumers can see the company and its resources. On account of this, corporate image is of great importance for most service companies. Consumers' expectations are influenced by their view of the company, namely the image (Grönroos, 1984). 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 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). If a company has a better image than other competitors, customers will be more willing to use that company's products and services (Kuo & Tang, 2013; Loudon David & Della, 1993). The Web of Science has 1436 articles on both SEM and image. The most cited articles which used image as a factor in their studies can be listed as Andreassen and Lindestad (1998), Bigne et al. (2001), Chen and Chen (2010), Chi and Qu (2008), Park et al. (2006), Ryu et al. (2012), and Yoo et al. (2000).

2.2.4 Trust

Trust in commercial relations is defined as the reliance on the reliability and integrity of the other party (Ozer & Aydin, 2004). Because the customer carries risk in his/her decisions, trust is a tool that facilitates decision-making in case of confusion (Lewis & Weigert, 1985). Trust; believing in the brand before the intention to buy a brand (Eren & Erge, 2012). 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, 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). Loureiro and González (2008), Dagger and O'Brien (2010), Akamavi et al. (2015), Su et al. (2017), and Schlesinger et al. (2017) used the factor ‘trust’ in their studies, and these are some examples using trust as a factor. According to a query conducted with both SEM and trust in Web of Science, 2441 articles (SCI-E and SSCI) have been produced by the authors so far. Cannon and Perreault Jr (1999), Colquitt et al. (2007), Kim et al.

(2008), Malhotra et al. (2004), and McEvily and Zaheer (1999) have been the most popular articles among them.

2.2.5 Satisfaction

The attitude that a consumer develops as a result of evaluating the consumption experience with a particular product is called customer satisfaction or dissatisfaction. Satisfaction resulting from the purchase and consumption of a product is very important for the producing side. This is because satisfaction ensures that the supplied product is linked with post-purchase events such as behavior changes, repeated purchases, and brand loyalty. In every sector where intensive competition conditions are experienced, organizations have to give importance to customer satisfaction to keep their existing customers and win new ones (Yalcin & Kocak, 2009). Customer satisfaction is a crucial element of the repurchase decision (Golbasi Simsek & Noyan, 2009; Kasmer, 2005). It is the most effective element of the company or brand in communication with the target market and, at the same time, the lowest cost. Satisfied customers can tell their satisfaction to potential customers, while unsatisfied customers can tell their complaints and dissatisfaction with those around them (Dubrovski, 2001). According to a query result with both SEM and satisfaction in Web of Science, Cronin Jr et al. (2000), Jarvis et al. (2003), Morgan and Hunt (1994), Preacher and Hayes (2008), and Schaufeli and Bakker (2004) have been the most remarkable articles out of 7216 articles (SCI-E and SSCI).

3
METHODS

3.1 Structural Equation Modeling

The structural equation modeling technique examines the structure of interrelationships expressed through a series of equations to help explain relationships between variables. SEM, unlike other multivariate techniques, examines multiple relationships at once; as a result, it is a technique that tests a set of hypotheses while taking into account all possible information (Hair et al., 2010). There are two parts to the model. One of them is a measurement model that evaluates items as linear functions of factors (Irtema et al., 2018), the other is a structural model which shows the direction and strength of the relationships between latent variables. Latent variables are variables that cannot be observed directly but can be created after inferring through observed variables. They are divided into two categories in SEM; exogenous and endogenous latent variables. An example of each latent variable type is given in Figure 3.1. In addition, an example of structural model is given in Figure 3.2 and the definitions of the symbols are given in Table 3.1.

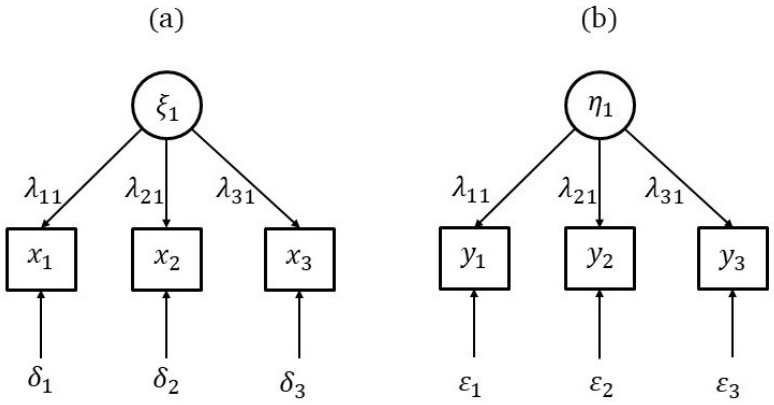


Figure 3.1 Example of exogenous (a) and endogenous (b) measurement model

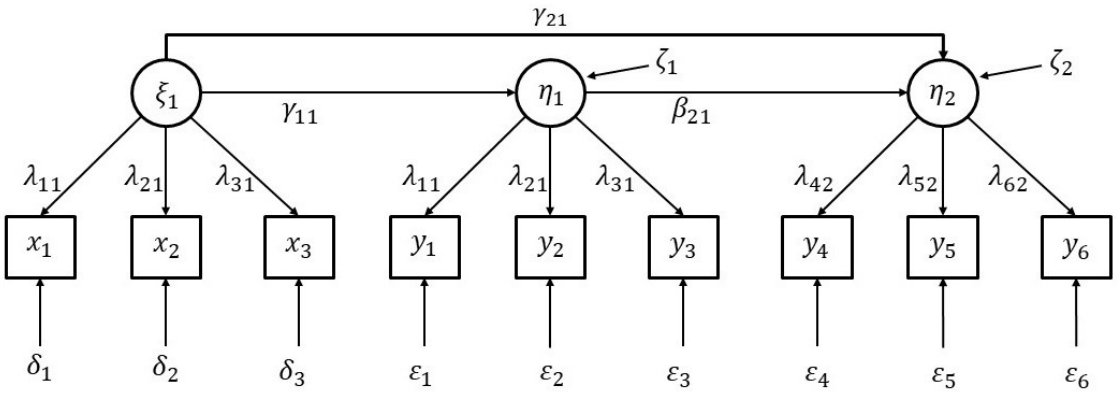


Figure 3.2 An example of a structural model

Table 3.1 Definitions of the symbols in SEM

Symbols	Definition
x	Observed exogenous variable
y	Observed endogenous variable
ξ (Ksi)	Latent exogenous variable
η (Eta)	Latent endogenous variable
λ (Lambda)	Regression coefficient between latent and observed variable, that is factor loading
δ (Delta)	Measurement errors in observed exogenous variable
ε (Epsilon)	Measurement errors in observed endogenous variable
ζ (Zeta)	Structural disturbances
γ (Gamma)	Structural coefficients from any ξ to any η
β (Beta)	Structural coefficients from any η to another η

Overall, SEM has some general characteristics. These are briefly (Gazeloglu, 2016),

- It enables the measurement of regression coefficients in the theoretical model by controlling the effects of measurement errors arising from the relationships in hypotheses,
- It allows testing the suitability of the theoretical model with the data obtained as a result of the experiment,
- It provides the opportunity to test different estimates of measurement errors,

- Different factor structures can be tested and compared with different groups. In this way, it allows trying out different theoretical models and determines which of them is more suitable for the data obtained,
- Many regression analyses can be combined simultaneously,
- SEM allows the testing of non-standard models. As in time series analysis, it can test by allowing autocorrelation of measurement errors,
- It allows to determine the relationships between latent variables and shows indirect and direct effects between variables and total effect,
- It minimizes measurement error by assigning multiple observed variables to each latent variable, testing reliability, and using confirmatory factor analysis,
- It has a graphical interface that provides a better understanding of the model. It not only tests the model through coefficients but also has the opportunity to test the model as a whole,
- It has the ability to explain the mediator variables that fall between cause and effect relationships.

According to Li (2015), SEM is expressed by some researchers as the summation of multiple regression, path, and confirmatory factor analyses. The assumptions of structural equation modeling are as follows,

- A reasonable sample size,
- Consecutive normal endogenous variables,
- Identification of model,
- Complete data (or incomplete data with proper handling),
- Explanation of model and the theory of the causal relationship

A multivariate statistical methodology for extracting factors from items is factor analysis. Confirmatory factor analysis (CFA), which includes sensible constraints into the model and excludes forced ones of exploratory factor analysis (EFA), is a special case of SEM used for the estimation of the measurement model. The model's parameters are estimated using a covariance analysis method, which aims to obtain model parameters that minimize the differences between the predicted

and observed variance-covariance matrices while respecting the model's constraints. The estimation method may be chosen considering various assumptions about the probability distribution, the scale properties of the variables, the complexity of the SEM, and the sample size (Golob, 2003). Because defining the relationships between the latent variables in model construction is made by the researcher, SEM is confirmatory rather than exploratory. In the next subsections, brief information about factor analysis, path analysis, and assessing the model fit in SEM is provided.

3.1.1 Factor Analysis

The most important task in factor analysis is to solve the set of variables expressed with a linear structure and divide the useful ones into small groups and collect them under the name of factor. In addition, factor analysis offers ease of creating variables with some solution between correlations (Mazmanoglu, 1979). The variables taken for factor analysis are called the observed variable, and each of the factors created as a result of the analysis is called the latent variable, as mentioned in Section 3.1. Factor analysis is classified into two categories. The first is EFA, whereas the second is CFA. A researcher may use the EFA to investigate the number of factors suitable for the data and which variables should be attributed to which factor. In some studies, it is possible for experts to know which variable belongs to which factor and proceed directly to the CFA phase. However, applying the EFA to the data before going into the CFA phase may significantly improve the SEM results. Apart from that, a researcher may use EFA to get a better understanding of the existing data. CFA is performed to determine whether observed variables represent the latent variables well.

3.1.2 Path Analysis

Path analysis presents both graphical and causal ways of SEM. The first application of SEM could date back to (Wright, 1918). A simple path diagram is given in Figure 3.3. A more detailed diagram than this was given in Figure 3.2. As given in Figure 3.3, the arrows shown from one factor to another indicate the presence of a relationship or a causal path. According to Figure 3.3, A causes C, B causes D, and C causes D. A and B are called endogenous, C and D are called exogenous

variables. In Figure 3.3, the double-headed arrow between A and B represents the correlation or covariance between the two variables. The path from A to D is referred to as an indirect path, whereas the path from C to D is referred to as a direct path. There must be an endogenous latent variable between the two latent variables for a path to be an indirect path.

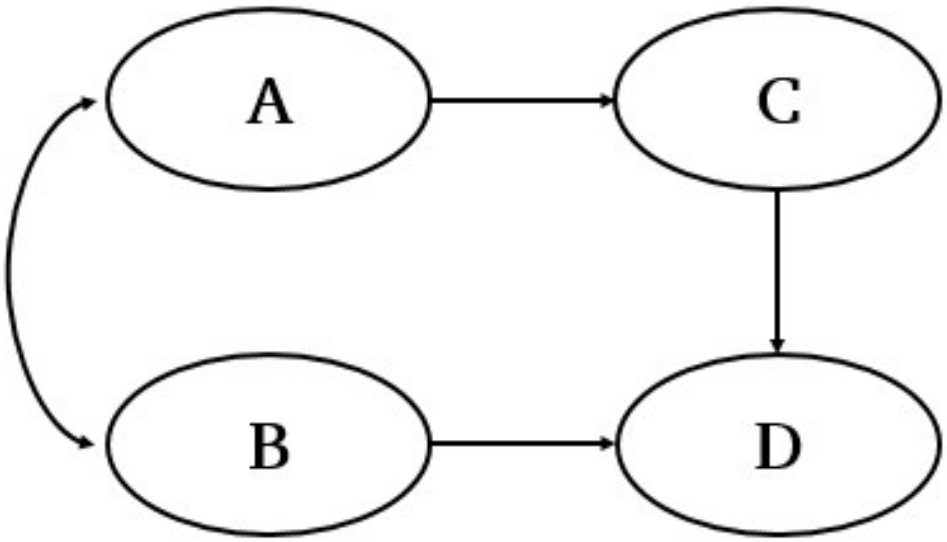


Figure 3.3 An example of a path diagram

3.1.3 Assessing the Model Fit in SEM

In SEM, there is no single significance test to test the validity of a model, so it is essential to evaluate multiple criteria together. Because of that, assessing the model fit in SEM is not as simple as in conventional statistical methods. These evaluation criteria are expressed as model goodness-of-fit indices. There are many goodness-of-fit indexes for evaluating the consistency of the relevant model in a study with empirical data (Schermelleh-Engel et al., 2003). While only the χ^2 test is available for inferential statistical evaluation, there are three criterion classes for descriptive evaluation, and these are overall model fit, model comparison, and model parsimony measures. Most descriptive fit criteria are based on χ^2 given by the sample size and optimized fitting function (Schumacker & Lomax, 2004).

The χ^2 test statistic is described as a test of significance, root mean square error of approximation (RMSEA), root mean square residual (RMR), and standardized

RMR (SRMR) are described as overall model fit measures. Normed fit index (NFI), non-normed fit index (NNFI), comparative fit index (CFI), goodness-of-fit index (GFI), and adjusted goodness-of-fit index (AGFI) are described as model comparison measures. Parsimony goodness-of-fit index (PGFI), parsimony normed fit index (PNFI), Akaike information criterion (AIC), the consistent Akaike information criterion (CAIC), and the expected cross-validation index (ECVI) are described as model parsimony measures (Schermelleh-Engel et al., 2003).

3.1.3.1 Test of Significance

Although the goodness-of-fit indices used in SEM programs vary, the most commonly used statistics that can be accepted as the initial goodness-of fit-index is χ^2. The χ^2 test is the test of the appropriateness between the data and the model, in other words, the χ^2 tests the hypothesis of whether the developed model differs from the model that appears in the covariance structure of the observed variables. As long as the χ^2 value calculated as a result of the test is small, it is decided that the appropriateness between the data and the model is proper. Also, since this value is a difference value, if χ^2 is meaningful, it is interpreted that the two models differ significantly from each other.

3.1.3.2 Indexes of Overall Fit Measures

RMSEA is used to determine the lack of appropriateness of the specified model according to the sample. The RMR index is the square root of the mean-squared differences between the covariance matrix calculated from the theoretical model and the sample covariance matrix. RMR is a badness-of-fit index based on the fitted residuals, and the values close to zero mean a good fit (Schermelleh-Engel et al., 2003). Since it will be more difficult to evaluate the model appropriateness and make interpretations when the non-standardized variance-covariance matrix is used, it is recommended to use a standardized version of RMR, which is called SRMR, instead of RMR (Cangur, 2012).

3.1.3.3 Model Comparison Measures

The NFI fit index proposed by Bentler and Bonett (1980) is expressed as the ratio of the target model to the value of the independent model. In other words, NFI

evaluates the model by comparing the value of the model with which all measured variables are independent and the value of the target model. Because the NFI index is affected by the sample size, the NNFI index has been developed by Bentler and Bonett (1980). They proposed an NNFI index, which is also known as the Tucker-Lewis index (TLI), by developing a number of studies by Tucker and Lewis (1973). CFI is an adjusted version of the Relative Noncentrality Index (RNI) suggested by McDonald and Marsh (1990). CFI was developed by Bentler and Bonett (1980) to prevent the underestimation of the model fit in small samples of the NFI index. In the CFI, the target model and the independent model are compared. GFI (Joresköb & Sörbom, 1989; Tanaka & Huba, 1984) is a measure of the fit between the variance-covariance matrix of the observed variables and the estimated variance-covariance matrix. GFI expresses how well the target model fits compared to the independent model (Kus, 2014). AGFI was developed by Joresköb and Sörbom (1989) to adjust the bias that model complexity caused in the GFI. It adjusts the degrees of freedom relative to the number of items. It, therefore, rewards less complicated models with fewer parameters.

3.1.3.4 Model Parsimony Measures

PGFI (Mulaik et al., 1989) and PNFI (James et al., 1982) are the modified versions of GFI and NFI, respectively. Both indexes take values between 0 and 1. Both indexes take values between 0 and 1, and high values of these indexes indicate a more parsimonious fit. They may be used to choose the better model between alternative models. AIC, CAIC, and ECVI values could also be used to choose the better model between alternative models. When choosing between multiple models, the model with the smallest value means that that model has the best fit.

Although there is no established guideline in which cases appropriateness is achieved in SEM, there are some basic rules for indexes in the literature. Table 3.2 shows the acceptable values for the goodness of fit indices mentioned above.

Table 3.2 Model goodness-of-fit indices and their admissibility limits

Index	Abbreviation	Admissibility
Chi-Square / Degrees of Freedom	Chi-Square (χ^2) / df	$0 < \chi^2/df < 5$
Root Mean Square Error of Approximation	RMSEA	< .08
Standardized Root Mean Square Residual	SRMR	< .10
Normed Fit Index	NFI	> .90
Non-normed Fit Index	NNFI/TLI	> .95
Comparative Fit Index	CFI	> .90
Goodness-of-Fit Index	GFI	> .90
Adjusted Goodness of Fit Index	AGFI	> .85
Parsimony Goodness-of-Fit Index	PGFI	the smallest
Parsimony Normed Fit Index	PNFI	the smallest
Akaike Information Criterion	AIC	the smallest
Consistent Akaike Information Criterion	CAIC	the smallest
Expected Cross-Validation Index	ECVI	the smallest

Source: Azim et al. (2012) & Schermelleh-Engel et al. (2003)

It should be noted that these restrictions are arbitrary and should not be treated seriously. Goodness-of-fit indices can be affected by the effects of normality and independence violations and the estimation method effects, model misspecification, and small-sample bias (Hu & Bentler, 1998; Schermelleh-Engel et al., 2003). In model evaluating, a 2-index representation strategy is recommended by Hu and Bentler (1999) by using the combination of NNFI (TLI), RMSEA or CFI along with SRMR to evaluate the goodness of fit of the model. It is the combination of rules as SRMR ≤.09 and NNFI ≥ .96, or SRMR ≤.09 and RMSEA ≤ .06, or SRMR ≤.09 and CFI ≥ .96, to provide a good fit of the model (Hooper et al., 2008). SEM has been utilized in various study fields, and it is now well established and widely used in the field of transportation. (de Oña et al., 2015).

3.2 Bayesian Networks

3.2.1 Definitions

Before discussing the BN subject, it is essential to explain BN-related terms. The terms and explanations that should be known while being in touch with BN are as follows:

- Node: A node represents a random variable. In Figure 3.4, A, B, and C represent nodes.
- Edge: An edge represents a direct relationship between two nodes. In Figure 3.4, the arrows between A and B and between B and C are called edges.
- Parent Node: The parent node is a node that directs an arrow to any variable. In Figure 3.4, A is a parent node of B; B is a parent node of C.
- Child Node: A child node is a node that an arrow is directed from any variable. In Figure 3.4, B is a child node of A; C is a child node of B.
- Root Node: A root node is a node that has no parent nodes. In Figure 3.4, A is the root node, because it has no parent nodes.
- Leaf Node: A leaf node is a node that has no child nodes. In Figure 3.4, C is the child node because it has no child nodes.
- Directed acyclic graph (DAG): DAG is a visualization of a network with directed links and no loops. In Figure 3.4, the whole visualization is called DAG.



Figure 3.4 An example of a directed acyclic graph

3.2.2 Introduction to Bayesian Networks

Bayesian networks also called "Bayesian belief networks," "belief networks," "Bayes networks," or "decision network" in the literature is a method that visually presents conditional probability relationships of all variables in the given network. By handling a specific state of any variable in the network, that is, setting evidence to that state, the marginal probability values of the other variables in the network can be reached. In this way, it is possible to focus on a specific state or situation and investigate how the other variables in the network react in the presence of

this evidence. This process can be repeated for all other variables and all states of the variables. As a result of these processes, it is possible to obtain independent and interpretable different networks. In other words, the main purpose of using BN is to determine how the states of the other variables are affected when evidence is set to a state of any variable.

The concept of BN, as it is known today, was first introduced by Judea Pearl in 1985 (Pearl, 1985). It employs a directed acyclic graph (DAG), and the network structure of a BN is represented in DAG by nodes and arcs. BN is divided into two components that correspond to the qualitative and quantitative descriptions of the relationships among variables.

3.2.2.1 Qualitative Structure

This part is a DAG that consists of a series of nodes representing the variables and a series of directed arcs that show the presence of causal effects between variables in the network. DAG is also called loopless graphs. The reason why the DAG structure is called loopless graphs is due to the fact that causal relationships should never return to where the arrows eventually started. In a DAG, it should be impossible to return to the same node in any way when the path followed by an arrow from any node is followed. The structure of node chains is three types: chain, fork, and v-structure (Murphy, 2012). The chain structure in which the arrows between the variables are in the same direction is given in Figure 3.5(a), the fork structure where the arrows between the variables come out of a node is given in Figure 3.5(b), and the v-structure where the arrows between the variables go towards a node is also given in Figure 3.5(c).

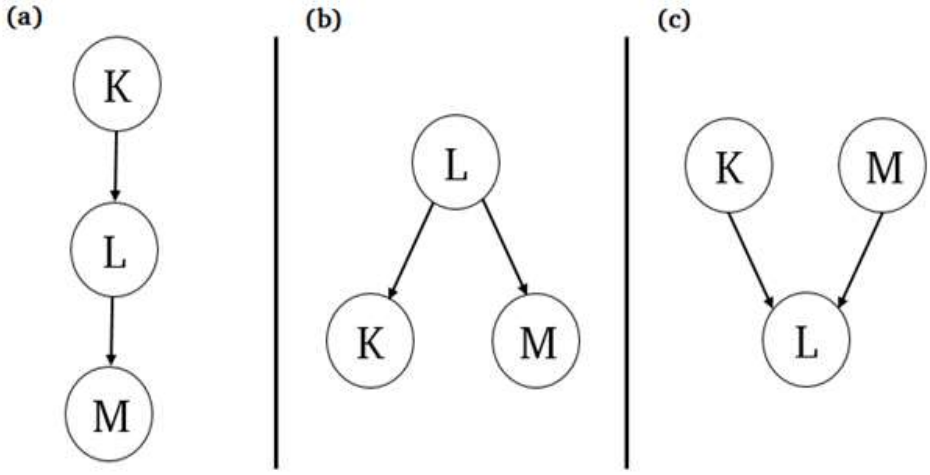


Figure 3.5 Structure of node chains: chain (a), fork (b), v-structure (c)

3.2.2.2 Quantitative Structure

The second part of BN is a conditional probability table (CPT), which describes the likelihood of a node's states given the node's current 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 fundamental property 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 (Eq. (1)) (Pearl, 2000):

$$P(X_{1,}X_{2,}X_{3,}\dots,X_{n,}) = \prod_{i=1}^{n} P(X_i|pa(X_i)), \quad (1)$$

Where X_i is the variable, and pa(X_i) are the parents of node X_i.

3.2.3 What-if Analysis: Interpretation in Bayesian Networks

There are two concepts that need to be explained before commenting on BN. One of them is "setting (entering) an evidence" on a specific state, and the other one is "posterior probability." Before explaining these concepts, a sample story is given as follows;

A seller selling ice cream at a popular tourist destination claims that the weather affects ice cream sales. This seller records the current weather and the sales status at the end of the day for 100 days in the place where he sold ice cream. The

Bayesian network created from the data obtained after 100 days is as in Figure 3.6(a). When the states in this simple network are examined, it is seen that the weather is cloudy in 19 of 100 days (%19), and the weather is open in 81 of 100 days. Likewise, when the ice cream sales status in the simple network in Figure 3.6(a) is examined, there are low sales in 21 of 100 days, medium sales in 25 days, and high sales in 54 days.

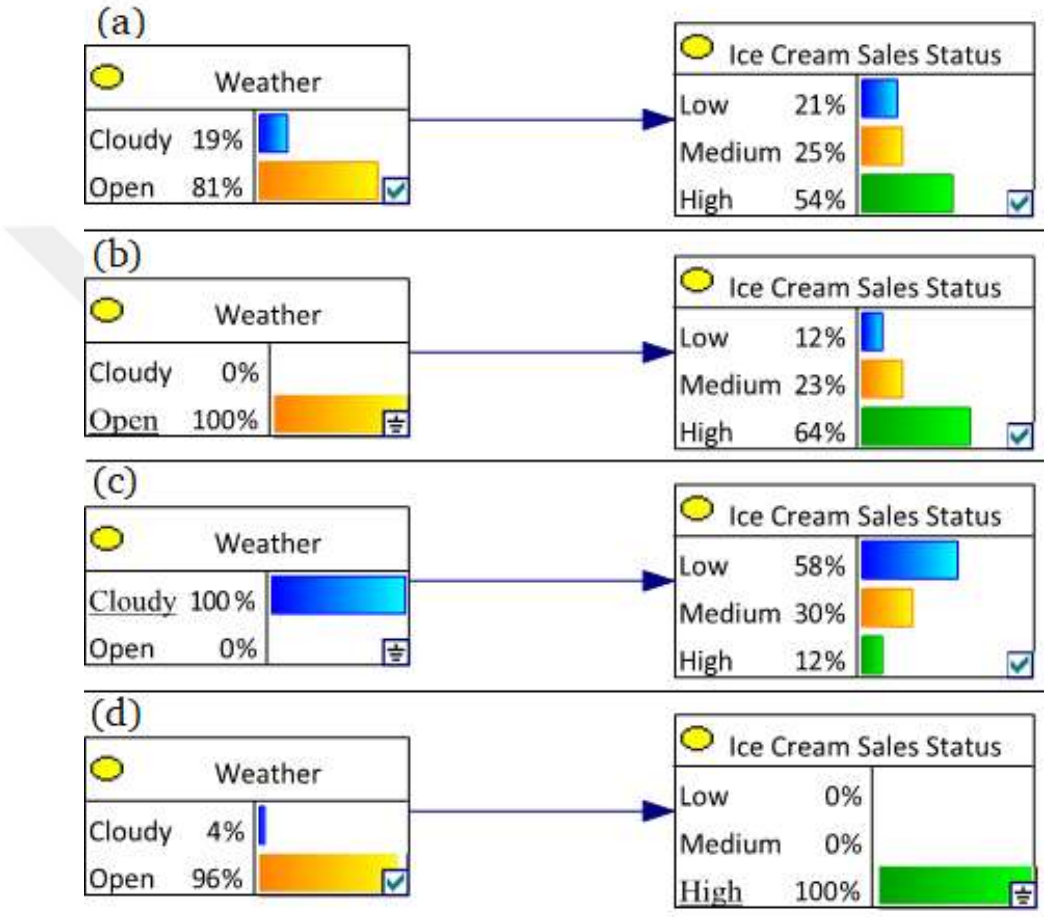


Figure 3.6 An example of evidence setting in Bayesian network

By setting evidence on a specific state in BN, the dynamic (flexible) side of this method also can be named as “what-if analysis” may be performed. While doing this, apart from all possible relationships in the network it can be seen how other variables react only in the presence of the state in which that evidence is set.

If an evidence is entered or set in a particular state of any parent node, that is, if the direction of the inference is from cause to symptom, this is called “predictive

reasoning.” The inference from the affected component (symptoms, child node) to the affected component (cause, parent node) is called “diagnostic reasoning,” which helps us figure out which causes would have led to a specific outcome (Lee & Hong, 2015). The diagnostic reasoning may be taken a step further by determining what the causes should be in order for the best outcome to occur.. This type of inference is called "prescriptive” (Yoo, 2017). Figure 3.6(b) and Figure 3.6(c) present the predictive reasoning, while Figure 3.6(d) presents the diagnostic reasoning and also prescriptive reasoning. If the evidence is set on the low or medium state of ice cream sales status in Figure 3.6(d), this inference would be named only diagnostic reasoning. Figure 3.6 (a) shows a simple example of BN. In Figure 3.6(b), an evidence is set on the state of the open weather. As a result of setting this evidence, new values on the states of other variables are called "posterior probability." So here, the seller wants to determine the status of the sales when the weather is only open. When the ice cream sales status is analyzed when the weather is clear, low, medium, and high posterior probability values are 12%, 23%, and 64%, respectively. So, according to this simple network, if the weather were always clear, the percentage of low sales would be 12% instead of 21%, while high sales would be 64% instead of 54%. Similarly, when examining the simple network in Figure 3.6(c), an evidence is set to the cloudy state of the weather variable. So this time, the seller wants to examine what the sales are like only when the weather is cloudy. When the ice cream sales status is examined in cases where the weather is cloudy, it is seen that the low, medium, and high posterior probability values are 58%, 30%, and 12%, respectively. So, according to this simple network, if the weather is always cloudy, the posterior probability of low sales would be 58% instead of 21%, and the posterior probability of high sales would be 12% instead of 54%. When Figure 3.6(d) is examined, an evidence is set to the high state of the ice cream sales status variable. Here, the seller wants to investigate the posterior probability values of the weather variable states when the sales were high. When the related network is analyzed, it is seen that the posterior probability of the open weather state is 96%, and the posterior probability of the cloudy state is 4%. So, when the seller made high sales, the

probability of open weather was 96%. These examples can be further increased, but with these short stories and the examples, the concepts of "setting evidence" and "posterior probability" have been tried to be explained thoroughly.

3.2.4 D-Separation

If an evidence is set to a specific state of L, the nodes K and M are conditionally independent in Figure 3.5(a). A similar situation is the same for the fork structure in Figure 3.5(b). In other words, if a specific state of L contains evidence, no information flows between K and M. For v-structure, if neither L nor any of its descendants contain evidence (Figure 3.5(c)), the nodes K and M are conditionally independent. This concept is identified as d-separation. It enables the definition of all conditional independences encrypted in a DAG structure and provides answers to questions such as “Are K and M conditionally independent given L?” or “Is the information about K unrelated for the belief about the state of M given information about L?” This concept is important in determining the connection types to be used when creating the network (Kucuker, 2018).

3.2.5 Learning Process in Bayesian Networks

In Bayesian networks, the researcher can determine the relationships between variables either with the help of the literature or taking into account expert opinions, or by learning from the existing data thanks to the algorithms proposed in previous studies, or by the mixture of these processes. When determining the relationships with the help of the literature, the relationships between the variables should have theoretical validity like SEM. Apart from this, if the researchers have not received sufficient support from the literature regarding the variables within the subject, or determined that the algorithms used for learning from the data are insufficient as a result of the high number of variables, they could include expert opinions in the study. After learning from the data, experts' opinions could also be included in the study. Also, as a result of insufficient data and high uncertainty, expert opinions could be consulted (Agarak, 2019). There have been lots of methods for learning BN from the data. They can be examined under three main topics, which are as follows: constraint-based, score-based methods, hybrid methods, and local discovery methods. In this thesis, the

“bnlearn” package in R is implemented for structure learning from the data, that is, knowledge extraction from the data (R Core Team, 2009)

Constraint-based algorithms construct the network structure by analyzing the probabilistic relationships required by the Bayesian networks with the conditional independence tests. Although the created models are learned from the observed data, they are usually interpreted as causal models. PC, grow-shrink, incremental association Markov blanket, fast incremental association, interleaved incremental association, max-min parents & children, and semi-interleaved hiton-pc algorithms are examples of constraint-based algorithms. Score-based algorithms assign a score to each Bayesian network and try to maximize this score with some heuristic search algorithms. Hill climbing and tabu search algorithms are examples of score-based algorithms. Hybrid algorithms and local discovery algorithms combine the aspects of score-based algorithms and constraint-based algorithms to construct the model. Max-min hill climbing and general 2-phase restricted maximization are examples of hybrid algorithms. Chow Liu and Aracne are examples of local discovery algorithms. For more detailed information about the bnlearn package, see Scutari (2009).

3.3 Probabilistic Structural Equation Modeling

A theoretical model representing causal paths between variables serves as the foundation for a structural equation model. The SEM researchers then design an experiment and gather data to check if the theoretical model they suggested is true, and if it is, they want to know what the coefficients are, which they then interpret. In practice, the initial theoretical model may be somewhat modified depending on SEM evaluation findings since the process of fitting the data to the models yields new information. If the measurement model in the CFA is unsatisfactory, this phase entails reviewing the model fit as well as parameter estimations and making revisions (which should be supported by the literature). Once the model is justified and the SEM gives appropriate findings, the estimated coefficients become the discussion points and drive arguments relating to the theoretical model.

Yoo (2018) proposed an approach called probabilistic structural equation model (PSEM) that the justified-SEM model was re-evaluated in BN. PSEM could be used to improve SEM by integrating it with dynamic probabilistic prediction capabilities of BN. For example, different inferences could be made by entering evidence into the network. The advantage of using BN is that it is possible to instantiate any variable without worrying about the direction of the relationships.

According to Yoo (2018), there are three different PSEM processes (Figure 3.7). These are PSEM, semi-PSEM and exploratory BN (EBN). BN can be reached as a result of a structure made by using classical SEM techniques, which are validated and confirmed with data and whose structure is hypothesized from theory. In other words, BN can be applied directly to the model created with classical SEM. The approach resulting from these processes is called PSEM.

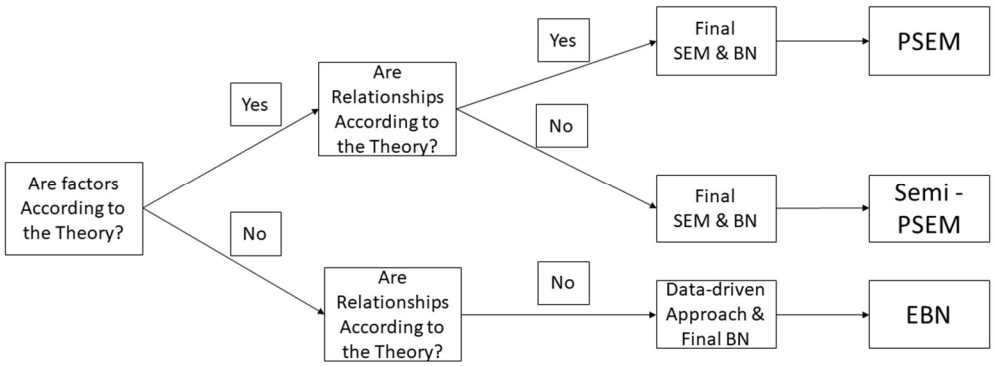


Figure 3.7 Probabilistic structural equation modeling processes (Yoo, 2018)

Another process is a data-driven approach, where the theory may not be sufficient in model building. Therefore, it can be used in cases where a comprehensive theory cannot exist. The structure obtained at this stage is called EBN since it is not based on theory as in SEM. Finally, the last approach in which the latent variables are created according to the theory, but the relationships among the latent variables are learned through learning from data exist. In this approach, neither theory is fully utilized, nor is there a data-driven perspective. Therefore, this approach is called semi-PSEM (Yoo, 2018).

In order to move to the semi-PSEM stage, a measurement model in which the items of the factors are determined must be created. The measurement model was created with EFA and CFA. After the measurement model was created, the categorization of the factor scores was performed by taking the averages of the items belonging to a factor. The categorization process was made as follows;

For an observation,

- If the mean of the factor was between 1 and 1.79, code as 1,
- If the mean of the factor was between 1.8 and 2.59 code as 2,
- If the mean of the factor was between 2.6 and 3.39, code as 3,
- If the mean of the factor was between 3.4 and 4.19, code as 4,
- If the mean of the factor was between 4.2 and 5, code as 5.

In this way, the categorization processes of the factor scores were completed. Before moving to the BN stage, the relationships between the factors were learned as prior knowledge with knowledge extraction from the data. The aim of this is to extract information from the data, which is a data-driven approach. The Bayesian Search algorithm was used with prior information to reach the final model. Afterward, the goodness-of-fit of the final BN model was tested. In the last part, different what-if analyzes were made, and the graphics were interpreted by making use of the dynamic probabilistic feature of the Bayesian network to make probabilistic interpretation. The stages of the analyses were given in Figure 3.8.

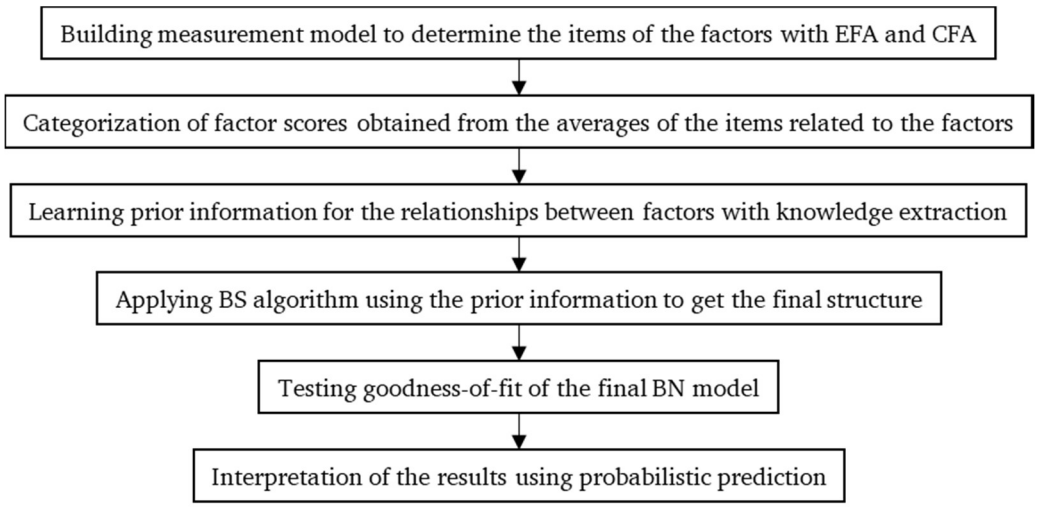


Figure 3.8 The stages of the study

4
DATA AND VARIABLES

A face-to-face questionnaire survey was conducted with a random sample of 900 HSRS passengers between Ankara and Eskisehir to collect data in the period from the middle of March until the end of April 2015 (Akyildiz Alcura et al., 2015). Twenty-nine items with a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5) were used to measure passenger perceptions of loyalty, trust, perceived value, image, and satisfaction in the study. All the questionnaires were responded to by HSRS users during the journey on the train. Valid and reliable data are vital both in the knowledge extraction step that imposes data-driven techniques and in the sense of SEM integration. Therefore, this study focuses on the responses of 239 passengers who frequently use HSRS at least several times a week. The demographic characteristics of the respondents were given in Table 4.1.

As seen from Table 4.1, of the 239 respondents, 61.1% were male. The age range of respondents is between 18 and 69. 26.4% of passengers are under the age of 24; 50.6% are between 25 and 35, 15.5% of passengers are between 36 and 45, 7.5% are older than 46. 53.1% of passengers stated their marital status as single. The majority of the passengers have an Associate/Bachelor's Degree (50.6%). The distribution of income shows that 42.7% of passengers' income is between 2501-5000 TL (approximately between 1070-2140 in 2015); then comes the income group of less than 2500 TL (approximately less than 1069$) with a percentage of 30.5%, and 11.7% of the passengers stated 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 this study are those who use HSRS frequently.

Table 4.1 Demographic characteristics of the respondents

Attributes	Distribution	Frequency	%
Age	≤24	63	26.4
	25-35	121	50.6
	36-45	37	15.5
	46-55	15	6.3
	56-65	2	.8
	≥65	1	.4
Gender	Male	146	61.1
	Female	93	38.9
Education Status	Primary School	2	.8
	Secondary School	7	2.9
	High School	42	17.6
	Associate or Undergraduate	121	50.6
	Master or PhD	67	28.1
Marital Status	Single	127	53.1
	Married	109	45.6
	Divorced/Widowed	3	1.3
Income Level	No income	28	11.7
	≤2500 TL*/month (≤1069$)	73	30.5
	2501TL – 5000TL /month (1070-2140)	102	42.7
	≥5001TL /month (≥2141$)	36	15.1
Frequency of HSRS usage	Everyday	86	36
	Several Times a Week	153	64

* *TL: Turkish Liras*

All the scales with corresponding measure items given in Table 4.2 were adapted or modified from the previous literature in order to fit the context of this study. The items measuring the image were adapted from Aydin and Ozer (2005), Johnson et al. (2001), and Yilmaz and Ari (2017); the items measuring the perceived value were adapted from Zeithaml (1988); the items measuring the trust were adapted from Aydin and Ozer (2005); the items measuring the satisfaction were adapted from Cronin Jr et al. (2000), Gustafsson and Johnson (2004), Hellier et al. (2003), Johnson et al. (2001), Levesque and McDougall (1996), Oliver (2000), Golbasi Simsek and Noyan Tekeli (2015), and Yilmaz and Ari (2017); the items measuring the loyalty were adapted from Aydin and Ozer

(2005), Chou and Kim (2009), Gallarza and Saura (2006), Johnson et al. (2001), Golbasi Simsek and Noyan (2009).

Table 4.2 Factors with items, factor loadings (EFA), and CFA estimates of the measurement model

Factors	Items (5-point Likert Scale)	Factor Loading (EFA)	Std. Factor Loading (CFA)	Std. Error	t value	R^2
Image_1	Steady company	.85	.87	.052	16.54**	.75
Image_2	Strong company	.90	.90	.047	17.51**	.81
Image_3	Well-established company	.77	.74	.057	13.12**	.55
Image_4	Preferable company	.69	.69	.064	11.77**	.47
Image_5	Useful for society	.74	.75	.054	13.17**	.56
Perceived Value_1	(The service provided) worth the price paid	.76	.75	.063	13.48**	.57
Perceived Value_2	(The service provided) worth the effort spent	.84	.84	.054	15.78**	.70
Perceived Value_3	Convenient the needs	.75	.77	.049	13.82**	.59
Perceived Value_4	(The comfort provided) worth the effort and money spent	.856	.83	.053	15.71**	.70
Perceived Value_5	(The safety provided) worth the effort and money spent	.83	.83	.052	15.60**	.69
Perceived Value_6	(The consistent and planned trip) worth the effort and money spent	.87	.87	.052	15.60**	.76
Perceived Value_7	Met the needs more than expected	.79	.79	.056	16.78**	.63
Perceived Value_8	(The service provided) worth the effort and money spent in general	.84	.85	.051	14.54**	.73
Trust_1	Honest company	.76	.78	.057	14.27**	.61
Trust_2	Responsible company	.78	.79	.057	14.55**	.63
Trust_3	Reliable employee	.86	.87	.049	16.79**	.76
Trust_4	Competent employee	.90	.90	.052	17.76**	.81
Trust_5	Honest employee	.92	.90	.051	17.91**	.82
Trust_6	Responsible employee	.87	.87	.054	16.79**	.76
Loyalty_1	Using again	.83	.80	.044	14.46**	.63
Loyalty_2	Recommendation to others	.94	.94	.048	18.81**	.88
Loyalty_3	Expression the pleasure	.73	.79	.059	14.22**	.62
Loyalty_4	Using more in future	.75	.76	.054	13.62**	.58
Satisfaction_1	Met the expectations	.79	.80	.057	14.47**	.64
Satisfaction_2	Better than the expectations	.78	.78	.059	14.06**	.61
Satisfaction_3	Satisfaction with duration	.78	.73	.063	12.80**	.54
Satisfaction_4	Satisfaction with comfort	.71	.73	.064	12.46**	.53
Satisfaction_5	Satisfaction with punctuality	.61	.58	.073	9.53**	.34
Satisfaction_6	General satisfaction (HSRS)	.82	.85	.050	15.87**	.72

** p< .1, Std.: Standardardized

5
RESULTS AND DISCUSSION

5.1 Measurement Model Results

The factors were needed to be measured to proceed to the PSEM stage and perform the analyses. The measurement model of the factors was formed in three steps: EFA, CFA, and reliability assessment. In this study, EFA was performed in SPSS 25.0 with principal axis factoring extraction and Promax rotation. Kaiser-Mayer-Olkin (KMO) and Bartlett's tests were conducted to test the adequacy and suitability of implementing factor analysis to the sample. KMO value was found as .948, which is defined as marvelous (Kaiser, 1974). According to Bartlett's test (Bartlett, 1950), the hypothesis that the correlation matrix is an identity matrix was rejected ($p<.01$). The factor analysis results of the items were found to be appropriate. As a result of these analyses, five factors were determined. When these factors were examined, they were found to be conceptually meaningful and acceptable according to factors handled in the literature. The factors with their items and the Promax rotation factor loadings of the items on the relevant factor are shown in Table 4.2. Most of the factor loadings were above .7 and reasonably high. The factors accounted for 78.814% of the total variance. All of the factor loadings of each variable met the minimum requirement of .30, ranging from .613 to .939 (Hair Jr et al., 1998). Based on high factor loadings, the five factors were accepted for further analyses. The CFA model was established for the five factors to test the measurement model and to determine if the items are significantly related to the factors. CFA model fit values were found as Chi-Square=874.84, d.f.= 367, p=.00, and RMSEA=.076. According to the 2-index representation method of Hu and Bentler (1999), the model with SRMR=.055, NNFI=.98, and CFI=.98 values were found to provide a good fit to the data. The CFA results, including standardized factor loadings, standard errors, t values, and R^2 values indicating item level reliabilities, are given in Table 4.2. The factor loadings were

higher than the offered value of .50, and most of them were found to be higher than the ideal value of .7 (Hair Jr et al., 1998; Hooper et al., 2008; Hu & Bentler, 1999). Since all the coefficients were found to be significant, the convergent validity of measurement was confirmed according to the CFA. Most of the R^2 values were higher than the suggested value of .5, having values in the range between .34 and .88, which shows that more than half of the variance of the items can be explained by the related factors.

Factors and their items were obtained by EFA and CFA. It is also possible to evaluate how variables are clustered with each other as a result of the EBN approach specified in section 3.3. As given in Figure 5.1, the data-driven approach shows us how the variables belonging to the same factor were clustered with each other. It is also seen that items were clustered in parallel with the measurement model using the greedy thick thinning algorithm, which is run by learning from data. In addition, we can observe the relationships between factors through sets of items through this process. The process shows us how relationships can be learned through data in case there is not sufficient theory about the relationships between factors.

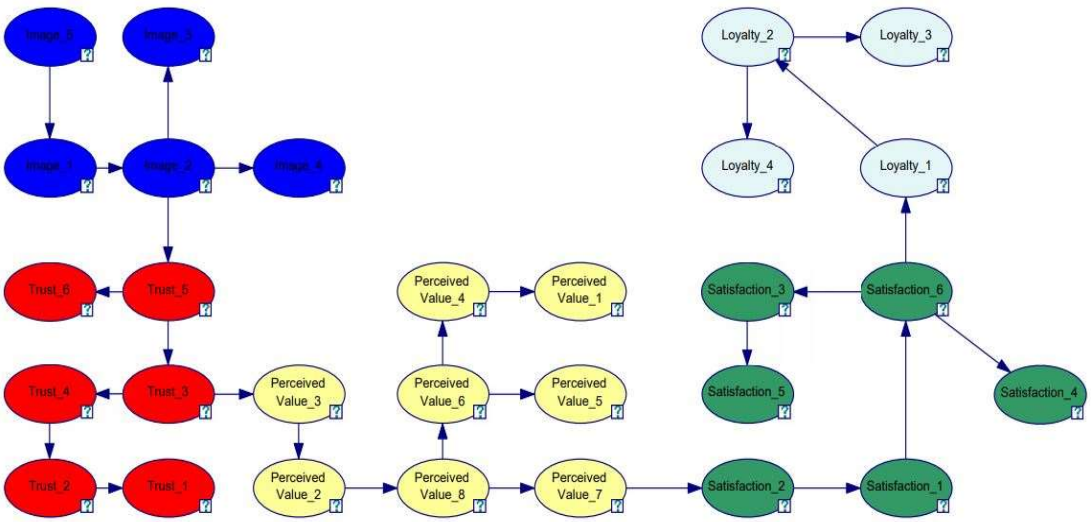


Figure 5.1 Clustering of variables using greedy thick thinning algorithm

For reliability assessment, Composite Reliability (CR) values were calculated using the standardized CFA results and can be seen in Table 5.1. The composite

reliability of the factors is reported here since it is generally acknowledged that CR is a better scale reliability measure than Cronbach's alpha (Cronbach, 1951). Since alpha tends to increase with the increase of the number of indicators and tends to decrease with non-equal factor loadings (Bagozzi & Yi, 1988) and these ranged between .86 and .95, indicating good reliability considering that .70 is the cut-off value for being acceptable (Nunnally & Bernstein, 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. A stricter approach for assessing convergent validity is the Average Variance Extracted (AVE) criterion proposed by Fornell and Larcker (1981). 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 higher than .50. So, at least half of the total variance of the items was 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 are presented in Table 5.1. When Table 5.1 is examined, it is seen that the AVE values of all factors are higher than .50. So, convergent validity is shown according to this strict approach. Based on these results, the factors were deemed acceptable. Factor scores obtained by averaging the original 5 point-Likert scale responses of the variables belonging to the same factor were re-categorized into five classes.

Table 5.1 Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) values

Factor	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Image	.89	.89	.63
Perceived Value	.94	.94	.67
Trust	.94	.95	.73
Loyalty	.87	.86	.68
Satisfaction	.88	.91	.56

5.2 Structure Learning Algorithms Results

In order to obtain prior information, 13 different structures were provided with the help of the structure learning algorithms included in the "bnlearn" package in R (R Core Team, 2009). This package includes various algorithms that may yield different results. The "bnlearn" implements constraint-based structure learning algorithms, score-based structure learning algorithms, hybrid structure learning algorithms, and local discovery algorithms. All the relationships in the structures formed by the algorithms were shown in Table 5.2.

Table 5.2 The results of the "knowledge extraction from the data" step

	Algorithms													
Relationships	PC	GS	IA	F.IA	I.IA	HC	TA	MH	RS	MP	SH	CH	AR	Tot*
TR → VA	1	1	1	1	1	1	1	1	1	1	1	1	1	13
SA → LO	1	1	1	1	1	1	1	1	1	1	1	1	1	13
TR → IM	1	1	1	1	1	0	1	0	0	1	1	1	1	10
SA → VA	1	1	1	1	1	0	1	0	0	1	1	1	1	10
LO → SA	1	1	1	1	1	0	0	0	0	1	1	1	1	9
IM → TR	1	0	0	0	0	1	0	1	1	1	1	1	1	8
VA → SA	1	0	0	0	0	1	0	1	1	1	1	1	1	8
SA → IM	1	1	1	1	1	0	1	0	0	1	1	0	0	8
VA → LO	1	0	0	0	0	1	1	1	1	1	1	0	0	7
LO → VA	1	1	1	1	1	0	0	0	0	1	1	0	0	7
IM → SA	1	0	0	0	0	1	0	1	1	1	1	0	0	6
VA → TR	1	0	0	0	0	0	0	0	0	1	1	1	1	5
TR → SA	0	0	0	0	0	1	1	0	0	0	0	0	0	2
IM → VA	0	0	0	0	0	1	0	0	0	0	0	0	0	1

IM: Image, TR: Trust, VA: Perceived Value, SA: Satisfaction, LO: Loyalty,GS: Grow-Shrink, IA: Incremental Association Markov Blanket, F.IA: Fast Incremental Association, I.IA: Interleaved Incremental Association, HC: Hill Climbing, TA: Tabu Search, MH: Max-Min Hill Climbing, RS: General 2-Phase Restricted Maximization, MP: Max-Min Parents & Children, SH: Semi-Interleaved Hiton-PC, CH: Chow-Liu, AR: Aracne, Tot: Total
* Totals equal to zero are not included in the table

In an algorithm, if the direct relationship to B from A denoted by A→B exists, it was coded as “1”, else “0”. After completing the coding for all relationships, when the sum of the A→B is 13, this relationship was considered to be used as prior information. The suggested relationships were obtained as follows:

1. Trust has a positive effect on perceived value
2. Satisfaction has a positive effect on loyalty

5.3 Semi-PSEM Results

Bayesian networks could be constructed via Graphical Network Interface (GeNIe) software (Druzdzel, 1999). GeNIe is a completely portable Bayesian inference engine developed by the Decision Systems Laboratory (http://www.bayesfusion.com/). The capacity to effectively construct and visualize BN is what gives GeNIe software its power (Cene & Karaman, 2015). The Bayesian Search (BS) method, one of the search & score algorithms available in GeNIe, was applied in this study to reach the final model provided by prior information gained from knowledge extraction from the data.

> “The BS algorithm is not deterministic, and it makes use of a given number of restarts from random sparse network layouts, finally returning the best network to the user” (Cooper & Herskovits, 1992; Tonda et al., 2013).
>
> “It performs a hill-climbing search with random restarts. Also, it uses the BDe metric for scoring candidate networks and uses the EM algorithm to learn parameters” (Cene & Karaman, 2015).

With the help of the BS algorithm in GeNIe, the learned structure can be seen in Figure 5.1. According to the final model, the relationships were obtained as follows:

1. Image has a positive effect on trust,
2. Image has a positive effect on loyalty,
3. Trust has a positive effect on perceived value,
4. Perceived value has a positive effect on satisfaction,
5. Satisfaction has a positive effect on loyalty.

These relationships were learned without using the literature, and this is one of the exclusive parts of this study. However, the classic SEM technique could be implemented in the final model to test the validity of the relationships.

Superficially, model fit values were found as RMSEA=.08, NFI= .96, NNFI= .97, CFI= .98, SRMR=.083. According to the 2-index representation method of Hu and Bentler (1999), the model values were found to provide a good fit to the data.

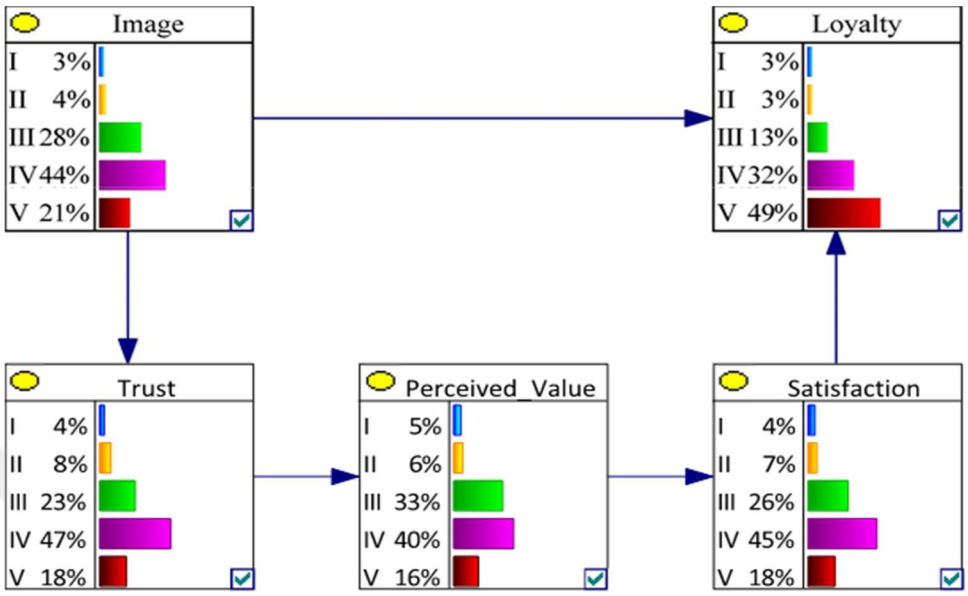


Figure 5.2 PSEM Results

In Figure 5.2, the states of “I,” “II,” “III,” “IV,” and “V” in the network corresponds to classes of "1", “2”, “3”, “4”, and “5” for completely dissatisfied, dissatisfied, neither satisfied nor dissatisfied, satisfied, and completely satisfied, respectively. The percentages in the boxes reflect the perceptions of the passengers involved in the study on the relevant factor. For instance, it is seen from Figure 5.2 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 trust perceptions of %18 of the passengers are "completely satisfied," and %47 of the passengers are "satisfied," so %65 of the passengers involved in this study trust the company. The trust perceptions of %4 of the passengers are "completely dissatisfied," and the trust perceptions of %8 of the respondents are "dissatisfied," so %12 of the passengers do not trust the company.

The perceived value perceptions of %16 of the passengers are "completely satisfied," and the perceived value perceptions of %40 of the passengers are "satisfied," so %56 of the passengers involved in this study generally satisfied with

the perceived value. The perceived value perceptions of %5 of the passengers are "completely dissatisfied," and the perceived value perceptions of %6 of the passengers are "dissatisfied," so %11 of the passengers generally dissatisfied with the perceived value.

The satisfaction perceptions of %18 of the passengers are "completely satisfied," and the satisfaction perceptions of %45 of the passengers are "satisfied," so %63 of the passengers involved in this study are satisfied with the company. The satisfaction perceptions of %4 of the passengers are "completely dissatisfied," and the satisfaction perceptions of %7 of the passengers are "dissatisfied," so %11 of the passengers are generally dissatisfied with the company.

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 loyalty perceptions of %3 of the passengers are "completely dissatisfied," and the loyalty perceptions of %3 of the passengers are "dissatisfied," so %6 of the passengers are not loyal to the company. In the next subsections, different what-if analyses will be applied to see the effect percentages of any factor on the other factors. While doing this, detailed interpretations also will be made.

5.3.1 The Effect of the Image

Figure 5.3(a) shows the changes in the network, given that the image is at its first state. After setting an evidence to the first state of the image, there were sudden changes over the states of the other factors. The changes in the probabilities of the states are the posterior probability values of the new network. According to the new model, the most prominent changes appeared in trust. The posterior probability of the lowest state of trust increased from %4 to %74. Based on these values, it could be said that the dissatisfaction of the image mostly affected the dissatisfaction of trust. It is also seen from Figure 5.3(a) that the first states of perceived value, satisfaction, and loyalty values were affected similarly by the change of image. The posterior probabilities of the lowest state of the 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 first state of the image increased the posterior probabilities of the first states of the trust, perceived value, satisfaction, and loyalty, especially increased the trust the most.

Figure 5.3(b) shows changes to the network, given that the image factor is at its highest state. This 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 to the fifth state of the image factor, there were sudden changes over the states of the other factors. According to the new model, the most significant changes occurred to loyalty and trust. The posterior probability of the fifth 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 5.2, and the changed model, Figure 5.3(b)). Based on these values, it could be said that the 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 loyalty feelings of the customers was to increase the image of the company.

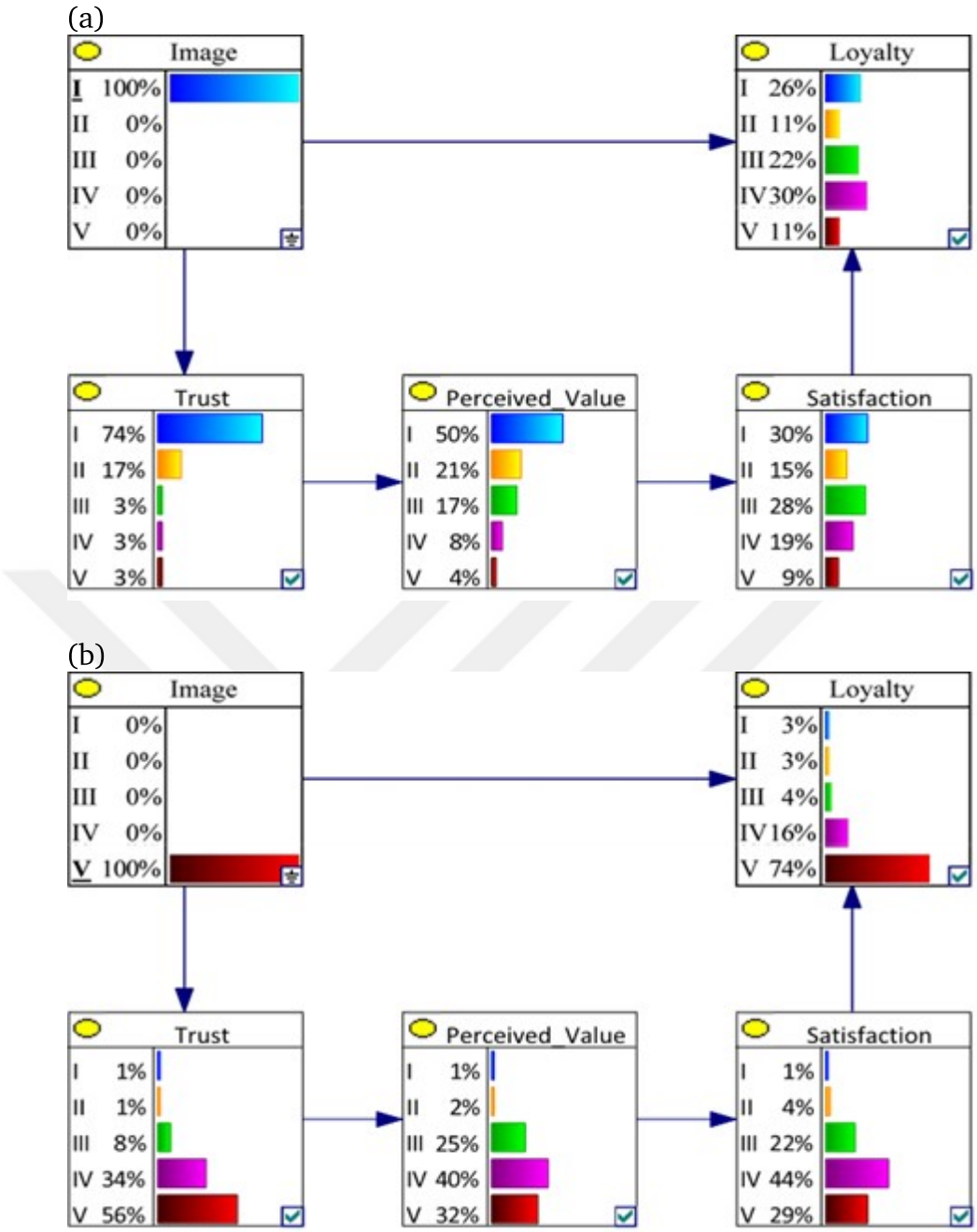


Figure 5.3 Changes in the network after setting an evidence on the lowest state (a) and the highest state (b) of the image

5.3.2 The Effect of the Trust

Figure 5.4(a) shows changes to the network, given that trust is at its first state. According to the new model, the most significant changes occurred to the perceived value. The posterior probability of the first 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 probability of the first state of satisfaction, image, and loyalty increased from %4 to %36, from %3 to %50, and from %3 to %22, respectively. Based on these values, it was seen that the first state of the trust increased the posterior probabilities of the first states of the image, perceived value, satisfaction, and loyalty, especially increased the perceived value the most.

Figure 5.4(b) shows changes to the network, given that trust is at its fifth state. According to the new model, the most significant changes occurred in the image and perceived value. The posterior probability of the fifth state of the 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. These values showed that the fifth state of the trust increased the probabilities of the fifth states of the image, perceived value, satisfaction, and loyalty, especially increased the image and perceived value the more.

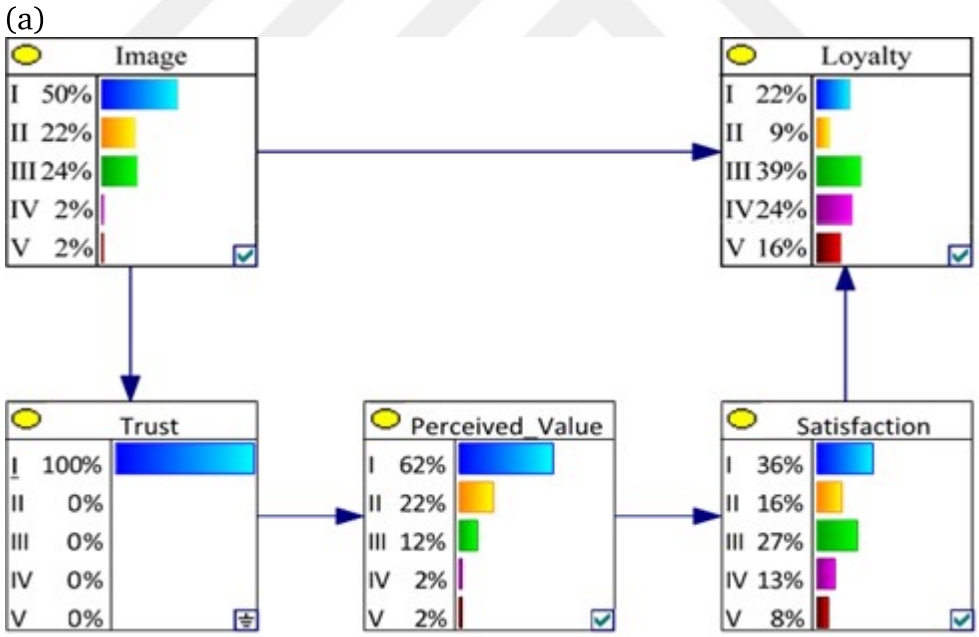


Figure 5.4 Changes in the network after setting an evidence on the lowest state (a) and the highest state (b) of the trust

(b)

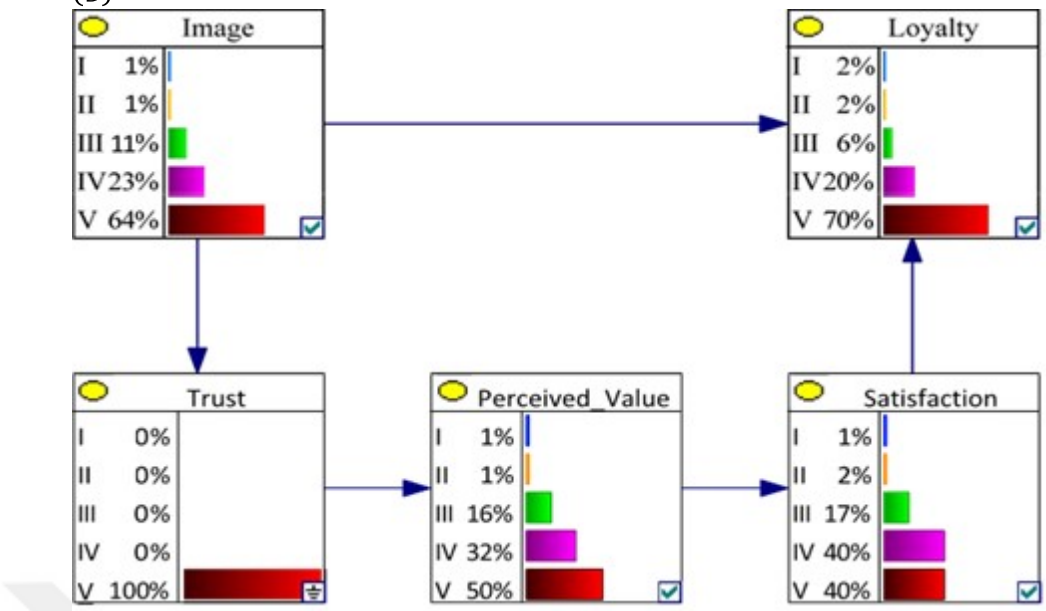


Figure 5.4 Changes in the network after setting an evidence on the lowest state (a) and the highest state (b) of the trust (continue)

5.3.3 The Effect of the Perceived Value

Figure 5.5(a) shows changes to the network, given that perceived value is at its first state. According to the new model, the most significant changes occurred to the satisfaction and trust. The posterior probability of the lowest state of satisfaction increased from %4 to %55. Based on these values, it could be said that the dissatisfaction of the perceived value mostly affected the dissatisfaction of the satisfaction factor. Besides, the posterior probability of the first state 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 first state of the perceived value increased the posterior probabilities of the lowest states of the image, trust, satisfaction, and loyalty especially increased the satisfaction the most.

Figure 5.5(b) shows changes to the network, given that perceived value is at its fifth state. According to the new model, the most significant changes occurred to the satisfaction factor. The posterior probability of the fifth state of the 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 fifth state of the perceived value increased the probabilities of the

highest states of the image, trust, satisfaction, and loyalty especially increased the satisfaction the most.

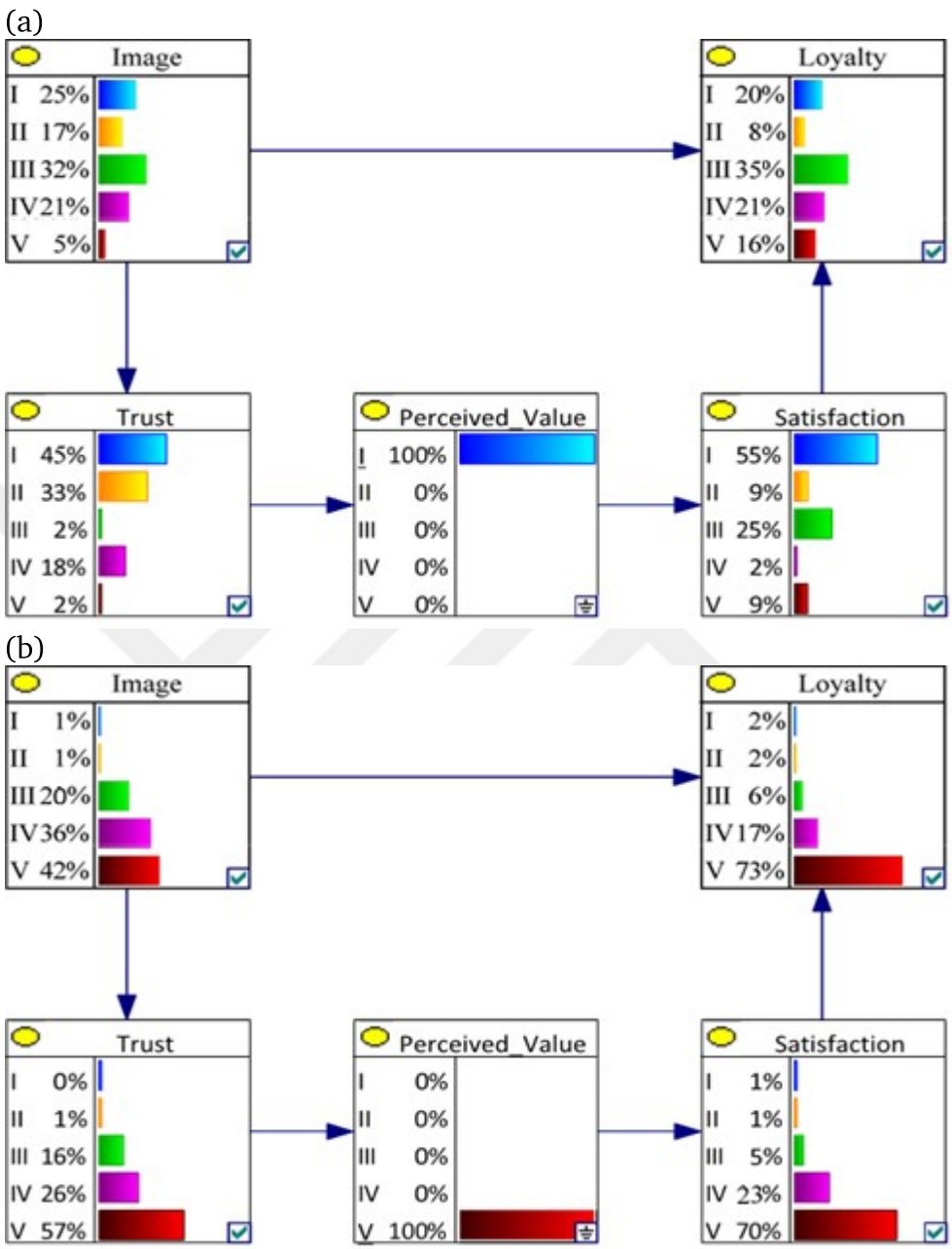


Figure 5.5 Changes in the network after setting an evidence on the lowest state (a) and the highest state (b) of the perceived value

5.3.4 The Effect of the Satisfaction

Figure 5.6(a) shows changes to the network, given that satisfaction is at its first state. According to the new model, the most significant changes occurred to the perceived value. The posterior probability of the first state of the image, trust,

perceived value, and loyalty increased from %3 to %19, from %4 to %35, the from %5 to %72, and from %3 to %27, respectively. These values show that the lowest state of the satisfaction factor increased the posterior probabilities of the lowest states of the image, trust, satisfaction, and loyalty, especially increased the posterior probability perceived value the most.

Figure 5.6(b) shows changes to the network, given that satisfaction is at its fifth state. According to the new model, the most significant changes occurred to the perceived value and loyalty. The posterior probability of the fifth 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. These values showed that the fifth state of the satisfaction factor increased the probabilities of the highest states of the image, trust, satisfaction, and loyalty.

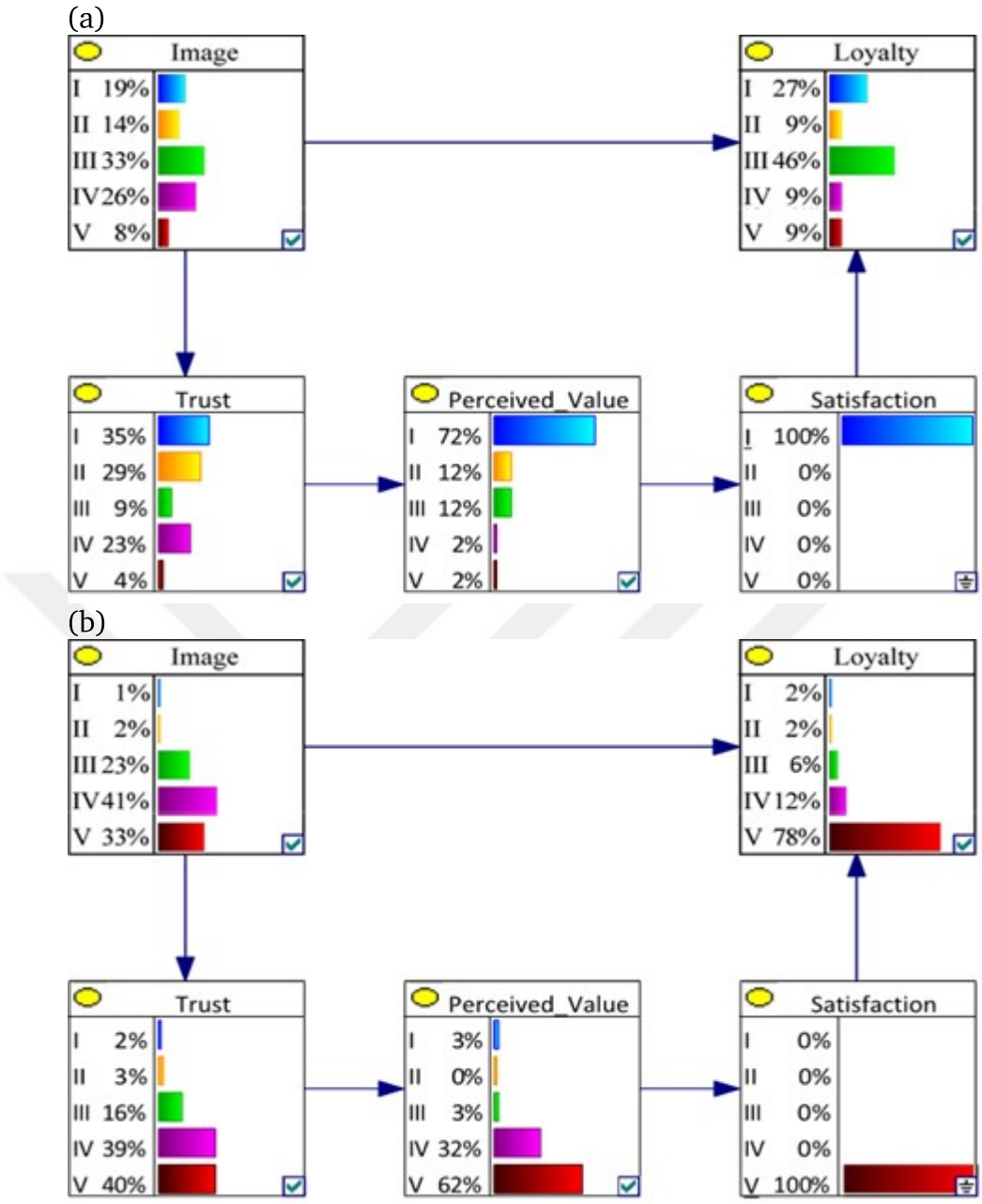


Figure 5.6 Changes in the network after setting an evidence on the lowest state (a) and the highest state (b) of the satisfaction

5.3.5 The Effect of the Loyalty

The changes to the network are given in Figure 5.7(a) when an evidence is set on the first state of loyalty. According to the network, the posterior probability of the first states of the image, trust, perceived value, and satisfaction increased from %3 to %22, from %4 to %28, from %5 to %35, and from %4 to %37, respectively. However, the posterior probabilities of the other states of the factors except loyalty were not found to be very different. For example, the probability values of the

states of the image from 1 to 5 were %22, %24, %15, %21, and %18, respectively. The differences in the values were not very different. The same circumstance could be said for other factors. The probability values of the states of the trust from 1 to 5 were %28, %18, %16, %26, and %12, respectively. The probability values of the states of the perceived value from 1 to 5 were %35, %13, %24, %18, and %10, respectively. The probability values of the states of the satisfaction from 1 to 5 were %37, %18, %14, %17, and %14, respectively.

The changes to the network can be seen in Figure 5.7(b) when an evidence is set on the fifth state of loyalty. According to the network, no abnormal changes could be seen over the posterior probabilities of the states of the other factors. Decreases or increases in the probabilities on the states were not as rapid as in the previous examples. The values of the first, second, third, and fourth states of the image decreased from %3 to %1, from %4 to %3, from %28 to %25, and from %44 to %40, respectively. The value of the fifth state of the image increased from %21 to %31. The values of the first, second, and third states of the trust decreased from %4 to %1, from %8 to %5, from %23 to %21, respectively. The value of the fourth state of the trust was the same (%47), the value of the highest state of the trust increased from %18 to %26. The values of the first, second, and third states of the perceived value decreased from %5 to %2, from %6 to %3, and from %33 to %26. The values of the fourth and fifth states of the perceived value increased from %40 to %45 and from %16 to %24, respectively. The values of the first, second, and third states of the satisfaction factor decreased from %4 to %1, from %7 to %1, and from %26 to %13, respectively. The values of the fourth and fifth states of the satisfaction factor increased from %45 to %56 and from %18 to %29. According to these values, it could be said that there were no sudden changes in the posterior probabilities of the states of the other factors. This result can be considered as support on why loyalty does not have an effect on the other factors.

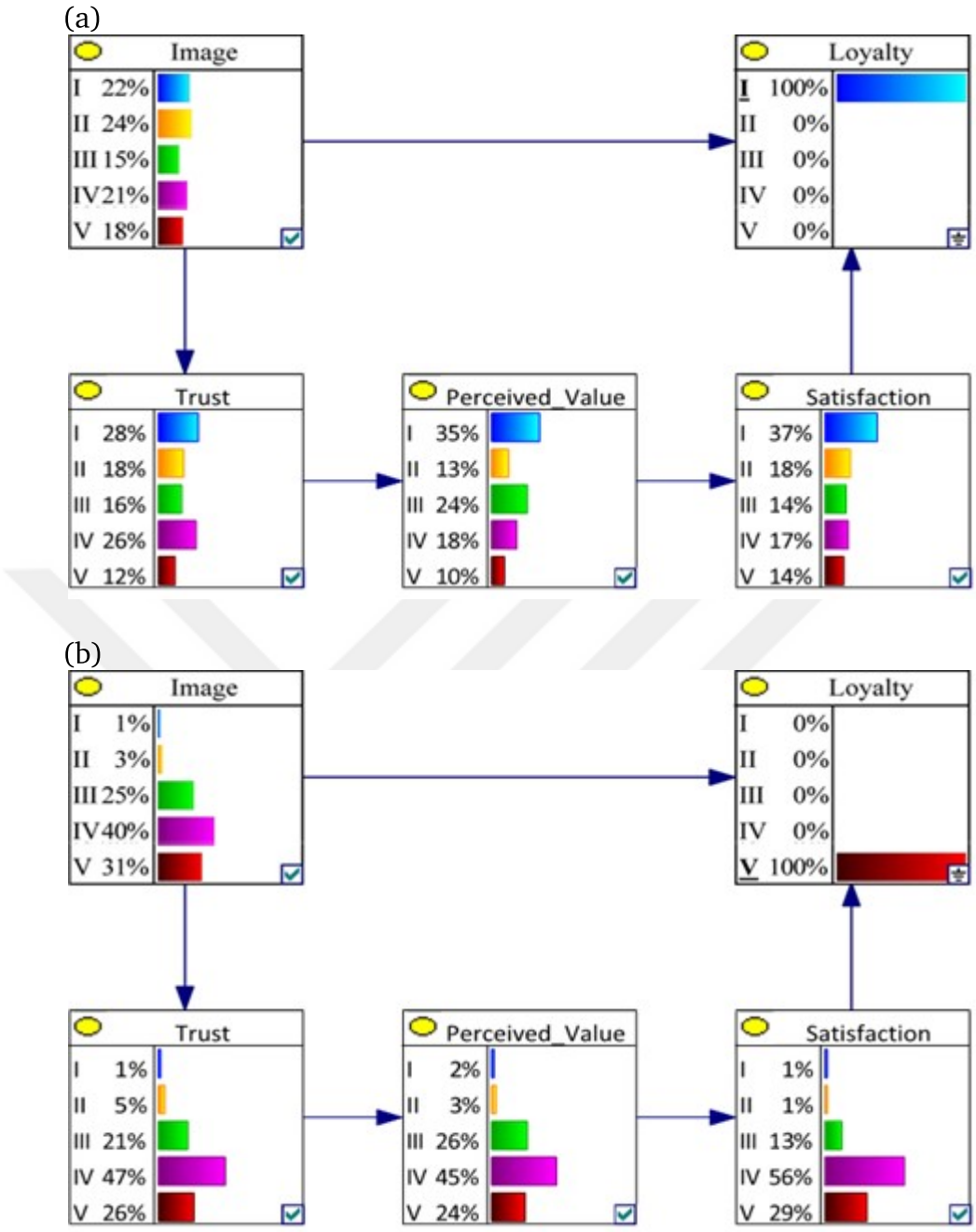


Figure 5.7 Changes in the network after setting an evidence on the lowest state (a) and the highest state (b) of the loyalty

5.3.6 Different Scenarios

In this subsection, beyond the graphics mentioned in the previous subsection, different scenarios will be analyzed. Only one piece of evidence was set for each Bayesian network in the previous subsection, instead of this, there will be evidence for more than one latent variable at a time in each Bayesian network in this subsection. Let's start by examining Figure 5.8 first. In Figure 5.8, it can be seen

how setting evidence on the first states of all variables except loyalty influences loyalty. In other words, the loyalty percentages of the passengers, who are stated to be completely dissatisfied with the image, trust, perceived value, and satisfaction, can be examined with this network. This network may answer the question: How do passengers who are fully dissatisfied in image, trust, perceived value, and satisfaction shape the loyalty factor towards the company? Although the dissatisfaction evidence is set to the latent variables, it is determined that the posterior probability of the fourth state and the fifth state of the loyalty variable are both %5. In other words, even if there is dissatisfaction for image, trust, perceived value, and satisfaction latent variables, 10% of the passengers stated that they are loyal to the company. Also, the posterior probability of the third state of loyalty is found to be %30. It means that 30% of the passengers are found to be undecided about whether they are loyal to the company. The posterior probability of the first state of the loyalty variable is %55, so %55 of the dissatisfied passengers are also not loyal to the company.

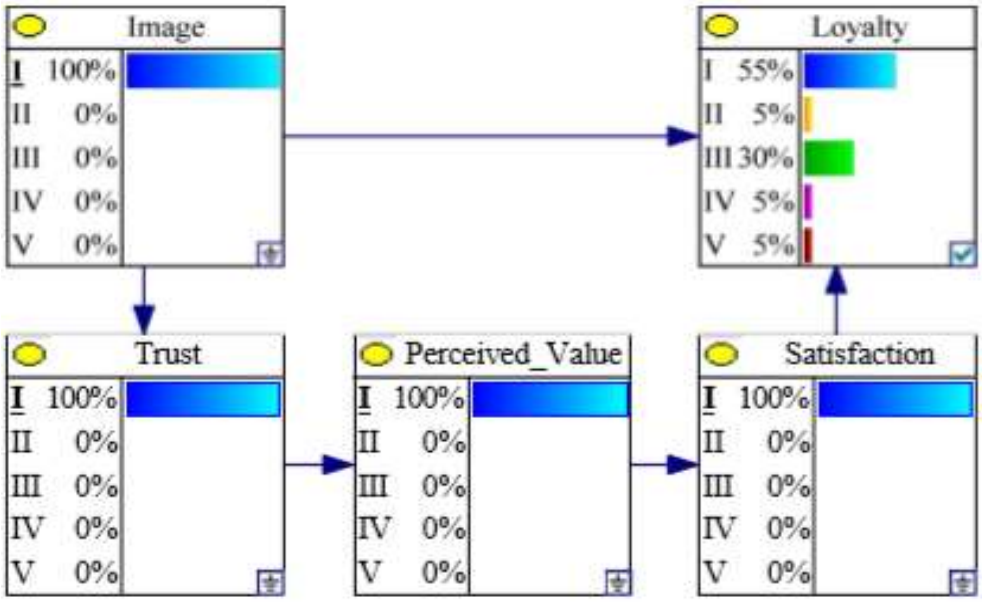


Figure 5.8 Changes in the network after setting evidence on the lowest states of image, trust, perceived value, and satisfaction

In Figure 5.9, it can be seen how entering evidence on the third states of image, trust, perceived value, and satisfaction influence loyalty. In other words, the loyalty percentages of the passengers, who are stated to be undecided (neither

dissatisfied nor satisfied) about the image, trust, perceived value, and satisfaction, can be examined with this network. 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 posterior probabilities of the fifth and fourth states of loyalty are %16 and %49, respectively. Based on these values, 65% of the passengers who are undecided about image, trust, perceived value, and satisfaction are found to be loyal to the company. In comparison, only a third (33%) of these are found to be unsure about loyalty to the company. Approximately 2% of passengers who are undecided about image, trust, perceived value, and satisfaction have been found to be not loyal to the company, and this value is negligibly small. 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.



Figure 5.9 Changes in the network after setting evidence on the third states of image, trust, perceived value, and satisfaction

In Figure 5.10, it can be seen how entering evidence on the fifth states of image, trust, perceived value, and satisfaction influence loyalty. In other words, the loyalty percentages of the passengers, who are stated to be completely satisfied with the image, trust, perceived value, and satisfaction, can be examined with this

network. 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 posterior probabilities of the fifth and fourth states of loyalty are %93 and %4, respectively. Based on these values, 97% of the passengers who are completely satisfied with image, trust, perceived value, and satisfaction are found to be loyal to the company. The posterior probabilities of the first and second states of the loyalty are both %1. So, only about %2 of the passengers stated that they are 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. The graphics in Figure 5.8, Figure 5.9, and Figure 5.10 can also be considered as supplements that demonstrate why the loyalty variable is the target variable.

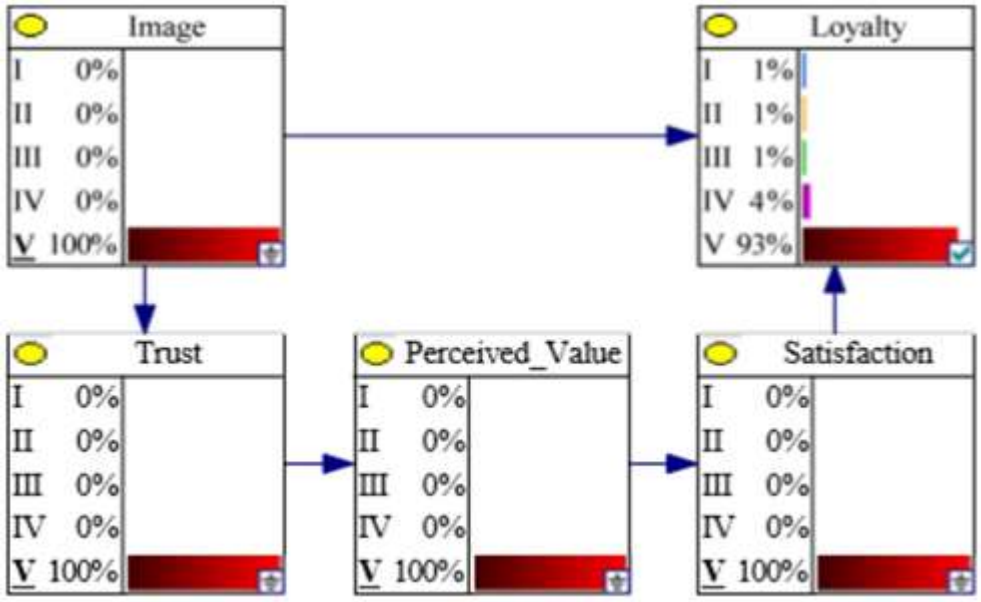


Figure 5.10 Changes in the network after setting evidence on the highest states of image, trust, perceived value, and satisfaction

5.4 Conclusions and Recommendations

In this study, it was aimed to conduct semi-PSEM, which is a particular case of PSEM that links SEM with BN, to investigate the relationships between HSRS passengers' satisfaction, loyalty, image, trust, and perceived value. The knowledge extraction algorithms were used to learn the relationships between the factors as

a data-driven approach in place of the causal link theory or the previous studies in the literature. The literature was used only to build a measurement model to score the factors. After getting the learned relationships gained from “knowledge extraction from the data” phase, the suggested relationships were used as prior information before implementing the BS algorithm in GeNIe. After the GeNIe phase, the final structure was obtained. According to the semi-PSEM results, the image has a positive effect on trust and loyalty, trust has a positive effect on perceived value, perceived value has a positive effect on satisfaction, and satisfaction has a positive effect on loyalty. The validity of the relationships was empirically supported by the goodness-of-fit measures of SEM. The model was found to provide a good fit to the data. The consistency of the relationships with the related literature was elaborately reviewed. The most prominent SEM studies that include the factors used in this study with their empirically supported relationships between them are given in the Appendix. 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 (see Appendix). As a conclusion, it can be said that our results were reasonable, coinciding with the SEM literature.

According to the results of the BN interpretation, the remarkable findings could be summarized as a recommendation to the managers/decision-makers in the transportation sector: When we know that the passengers’ image perception was completely dissatisfied, the posterior probabilities of the completely dissatisfied passengers about trust and loyalty increased from 4% to 74% and 3% to 26%, respectively. Additionally, when we know that the passengers’ image perception was completely satisfied, the posterior probabilities of the completely satisfied passengers about trust and loyalty increased from 18% to 56% and 49% to 74%, respectively. Thus, in order to make a noteworthy increase in passengers’ trust and loyalty, it is essential for companies to improve their image perceptions. Also, when we know that the passengers’ trust perceptions were completely dissatisfied and completely satisfied, respectively, the posterior probabilities of the completely dissatisfied and completely satisfied passengers about perceived value increased

from 5% to 62% and from 16% to 50%, respectively. As a result, in order to make a direct improvement in passengers' perceived value, companies need to increase passengers' trust. Further, when we know that the passengers' perceived value perceptions were completely dissatisfied and completely satisfied, respectively, the posterior probabilities of the completely dissatisfied and completely satisfied passengers about satisfaction increased from 4% to 55% and 18% to 70%, respectively. Based on these values, it can be concluded that in order to make a major increase in passengers' satisfaction, companies need to improve passengers' perceived value. When we know that the passengers' satisfaction perception was completely dissatisfied and completely satisfied, respectively, the posterior probabilities of the completely dissatisfied and completely satisfied passengers about loyalty increased from 3% to 27% and from 49% to 78%, respectively. According to these values, one of the shortest ways to increase the passengers' loyalty is to improve the passengers' satisfaction in addition to image. Finally, since no remarkable changes in the posterior probabilities of the factors were shown on the network, it was supported that loyalty is the target variable at the end of the sequence of the relationships.

The probabilistic predictive ability of the BN was used to investigate the effect of image, trust, perceived value, satisfaction, and loyalty perceptions of the HSRS passengers. 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, similar to the study of Díez-Mesa et al. (2018). In that study, they used the algorithms included in the "bnlearn" R package (Scutari, 2009). In an algorithm, if the direct relationship to B from A denoted by A→B exists, it was coded as "1", else "0". After completing the coding for all relationships, when the sum of the A→B corresponds to at least 65% of the total algorithms, they determined that this threshold value was sufficient in order to get the final model. Instead of this, it was decided to use a 100% value as a threshold in the current study. It means that if any relationship was not included in at least one algorithm, that relationship was considered to be absent in the first stage. In order to reach the final model provided by the prior

information, the Bayesian Search algorithm, which is one of the search & score algorithms implemented in the GeNIe, was used. The attractive part of this approach is that the appropriate model was built neither by the causal link theory nor by the previous studies in the literature but by the PSEM approach stated in the present study.

One of the contributions of the study is the utilization of the PSEM approach in model building. In the case of a researcher has no satisfactory knowledge/theory about the conceptual model, this approach may be useful in model building. The experts might have opportunities to evaluate the risks under different scenarios with the probabilistic predictive capabilities of the PSEM. The approach provides a more comprehensive perspective to decision-makers than traditional methods such as the SEM when exploring ways to increase behavioral intentions.

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A

THE RELATIONSHIPS BETWEEN IMAGE, SATISFACTION, TRUST, VALUE, AND LOYALTY ACCORDING TO THE PREVIOUS SEM STUDIES

Relationship*	Area	Source	Sample Size (Totally)
IM → LO	Education	Alves and Raposo (2007)	2687
IM → LO	Mobile Telecommunication Market	Aydin and Ozer (2005)	1662
IM → LO	Education	Brown and Mazzarol (2009)	373
IM → LO	Transportation	Brunner et al. (2008)	941
IM → LO	Hotel	Jani and 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	Andreassen and Lindestad (1998)	600
IM → TR	Restaurant	Chang (2013)	600
IM → TR	Tourism	Chen and Phou (2013)	428
IM → TR	Banking	Flavián et al. (2005)	633
IM → TR	Tourism	Loureiro and 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 and Raposo (2007)	2687
SA → LO	Education	Brown and Mazzarol (2009)	373
SA → LO	Transportation	Brunner et al. (2008)	941
SA → LO	Restaurant	Chang (2013)	600
SA → LO	Internet	Chang and Chen (2008)	334
SA → LO	Tourism	Chen and Phou (2013)	428
SA → LO	Transportation	Chi and Qu (2008)	345
SA → LO	Internet Service Providers	Chiou (2004)	209
SA → LO	Internet	Choi et al. (2008)	247
SA → LO	Transportation	Chou and Kim (2009)	418
SA → LO	Transportation	Chou et al. (2014)	1235
SA → LO	Marketing and Service Management	Coelho and Henseler (2012)	2104
SA → LO	Internet	Cyr et al. (2010)	270
SA → LO	Service Industry	Dagger and 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 and Johnson (2004)	260
SA → LO	Online Shopping	Chang and Wang (2011)	330
SA → LO	Transportation	Jang et al. (2013)	227
SA → LO	Hotel	Jani and Han (2014)	529

Relationship*	Area	Source	Sample Size (Totally)
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
SA → LO	Restaurant	Lee et al. (2009)	475
SA → LO	Tourism	Lee et al. (2008)	472
SA → LO	Online Shopping	Lin and Sun (2009)	200
SA → LO	Internet	Lin and Lee (2006)	200
SA → LO	Mobile Phone	Liu et al. (2011)	311
SA → LO	Tourism	Loureiro and González (2008)	679
SA → LO	Green Marketing	Martínez (2015)	382
SA → LO	Transportation	Minser and Webb (2010)	2439
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 and Miller (2007)	306
SA → LO	Restaurant	Ryu and Han (2011)	298
SA → LO	Education	Schlesinger et al. (2017)	1000
SA → LO	Transportation	Shen et al. (2016)	813
SA → LO	Marketing	Suh and Youjae (2006)	1940
SA → LO	Transportation	Sun et al. (2013)	498
SA → LO	Internet	Teng (2010)	865
SA → LO	Tourism	Andreassen and Lindestad (1998)	600
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 and Uysal (2005)	148
SA → LO	Hospitality	Yoon et al. (2010)	444
SA → LO	Tourism	Yuksel and Yuksel (2007)	241
SA → LO	Transportation	Zhang et al. (2019)	4702
SA → LO	Internet	Zhou and 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	K. Wu et al. (2015)	261
VA → SA	Education	Brown and Mazzarol (2009)	373
VA → SA	Restaurant	Chang (2013)	600
VA → SA	Tourism	Chen and Chen (2010)	477
VA → SA	Internet Service Providers	Chiou (2004)	209
VA → SA	Marketing and Service Management	Coelho and Henseler (2012)	2104
VA → SA	Online Shopping	Chang and Wang (2011)	330
VA → SA	Hospitality	Kassinis and Soteriou (2003)	104
VA → SA	Transportation	Lai and Chen (2011)	763
VA → SA	Transportation	Parahoo et al. (2014)	169
VA → SA	Airline Service	Park et al. (2006)	501
VA → SA	Restaurant	Ryu et al. (2012)	300
VA → SA	Transportation	Shen et al. (2016)	813

Relationship*	Area	Source	Sample Size (Totally)
VA → SA	Transportation	Sun et al. (2013)	498
VA → SA	Tourism	Andreassen and Lindestad (1998)	600
VA → SA	Transportation	Wen et al. (2005)	600
VA → SA	Hospitality	Yoon et al. (2010)	444
VA → SA	Transportation	Zhang et al. (2019)	4702
** IM: Image, LO: Loyalty, SA: Satisfaction, TR: Trust, VA: Perceived Value*			

PUBLICATIONS FROM THE THESIS

Conference Papers

1. Karadag, T., & Golbasi Simsek, G., (2019). "Probabilistic Structural Equation Modeling Approach to Investigate the Relationships between Passenger Perceived Value, Image, Trust, Satisfaction and Loyalty". y-BIS 2019 Conference: ISBIS Young Business and Industrial Statisticians Workshop on Recent Advances in Data Science and Business Analytics (pp.77). Istanbul, Turkey