The Comparison of Classical and Bayesian Structural Equation Models Through Ordered Categorical Data: A Case Study of Banking Service Quality

Gizem ERKAN[1], Murat DOGAN[2,*], Huseyin TATLIDIL[3]

[1] *Republic of Turkey Ministry of Youth and Sports, Ankara, Turkey*
[2] *Manisa Celal Bayar University, Department of Economics, Ankara, Turkey*
[3] *Hacettepe University, Department of Statistics, Ankara, Turkey*

Highlights
• The use of Bayesian estimation method in SEM is emphasized.
• Using sequential categorical data from a priori that do not contain information is explained.
• In terms of parameter estimation results, differences were found between ML and BSEM.

Abstract

This study aims to compare classical Structural Equation Modeling (SEM) and Bayesian Structural Equation Modeling (BSEM) in terms of ordered categorical data. In order to show the relationship between service dimensions and banks' customers' satisfactions, a data were analyzed with classical SEM and BSEM parameter estimation methods. In the Banking Service Quality Scale (SERVQUAL), which consists of sequential categorical data, classical SEM and BSEM were compared to evaluate customer satisfaction. In classical SEM, parameter estimations were made according to the Maximum Likelihood (ML) estimation method. In most of the studies using SERVQUAL in the literature, the results found in previous studies could not be used as prior informative because the service dimensions consisted of different number of factors. For this reason, considering that the results could yield similar results with the ML estimation method due to the high sample size, the use of conjugate prior was preferred instead of the non-informative prior due to the ordinal categorical nature of the data in the BSEM analysis. Since the questionnaire used in the study had a Likert type scale structure, the threshold values were calculated for ordered categorical data and used as prior informative. Thus, by using the threshold values obtained from the data set, a faster convergence of the parameters was achieved. As a result, service dimensions affecting satisfaction according to the ML parameter estimation method were found, Assurance, Physical Appearance, and Accessibility. In addition to these, Reliability as a service dimension was found to be also statistically significant in BSEM.

1. INTRODUCTION

Nowadays, instead of explanatory approaches, approaches aimed at discovering statistical relationships have become more prominent because while developing a model reflecting reality by explaining the relationship between observed and latent variables and associating causality, it is very important to refer to almost every field from social sciences to health sciences, from marketing to strategy [1, 2]. SEM is a very powerful statistical method that correlates latent structures. The aim of SEM is to test the hypothesis that the sample covariance matrix is equal for the set of measured variables. ($\Sigma = \Sigma(\theta)$) The calculation algorithm in the model was developed based on the sample covariance matrix S under the assumption of independent and asymptotically normal distribution of observations. According to this assumption, the distribution of the covariance matrix approaches the normal distribution if the relevant sample size is large. However, supporting these assumptions for researchers may not be possible in practice. Especially in studies conducted in fields such as medicine and psychology, it may not be possible to create a large sample or to provide multivariate normality in studies such as behavioral and social sciences where there are missing observations and categorical data structure is used, because in this case, parameter and standard error estimations will tend to give biased results.

*Corresponding author, e-mail: murat.dogan@cbu.edu.tr

In order to overcome these problems, many researchers started to use in their studies in the new period the Bayesian approach [3] on models that do not meet the classical SEM assumptions in SEM. Some of the methods developed are: SEMs with bivariate variables and/or SEMs having ordered categorical variables, Nonlinear or Two-stage Multilevel Mixture SEMs, SEMs with missing data, SEMs with variables coming from Exponential family distributions, Longitudinal SEMs, Semiparametric SEMs and Transformation SEMs [4, 5]. These studies not only prepare theoretical results but also try to produce important practical values. The BSEM technique, called Bayesian approach and based on the Bayesian approach, has been applied to substantive real research in various disciplines, including a much wider class of models, such as marketing research, diabetes research, medicine, psychology, coastal management and water quality, job satisfaction and life satisfaction [3, 6-12].

BSEM makes parameter estimations by using prior information and posterior distributions. Thus, it provides the most appropriate solution in cases where classical SEM is insufficient [13]. The use of BSEM has become widespread in recent years, especially with the development of computer programs that support MCMC (Monte Carlo Markov Chain) methods. Thus, it has been seen that the Bayesian approach in SEM provides some advantages to researchers. Since Bayesian methods expand the range of testable hypotheses, the results can be interpreted intuitively that does not rely on null hypothesis significance testing. In addition, the confidence interval estimations are interpreted over the probability of containing the relevant parameter in the classical approach, whereas in the Bayesian approach, the relevant parameter is interpreted over the probability of being within a certain range. In this way, the distribution and confidence interval of each relevant parameter can be created in the Bayesian approach. The Bayesian approach achieves better model fit by providing the necessary information with the help of informative prior instead of the initial assumptions in the classical approach. Because the use of prior informative both reduces model errors and provides updating of information since it combines previous findings with new data [14,15]. It provides more reliable results by providing useful statistics of posterior distribution such as mean and percentage, especially for small datasets, as it provides the use of real prior informative in addition to the existing information in the observed data [13, 16]. Moreover, unlike the classical approach, which relies only on the probabilities of the observed data, the Bayesian approach allows the estimation of parameters even when using priors that do not contain sufficient information, since it incorporates the previously obtained information into the parameter estimation along with the probabilities [17,18]. Since Bayesian analysis requires less computation, more and new model types can be analyzed [14]. In the classical approach, the unknown parameters are accepted as constants, whereas the Bayesian approach defines the unknown parameters as random variables. Thus, the Bayesian approach determines what can be inferred about parameter values, given the actually observed data. Bayesian analysis is a mathematically normative way of restoring reliability between parameter values as new data comes in.

In this study, classical SEM and BSEM methods were compared in terms of the Banking Service Quality Model consisting of sequential categorical data. In this regard, the satisfaction of university students with their banks was examined according to the banks' service dimensions. In this study, it is aimed to examine service dimensions, which are latent variables for satisfaction with banking services by considering both parameter estimation methods. Classical SEM analysis is used in the first part of the LISREL (Linear Structural Relations) application by using a package program. In the second part of the application, BSEM analysis was conducted by using the OpenBUGS package program by comparing classical SEM analysis.

2. MATERIAL METHOD

The data used in this research was collected from a survey of Eskisehir Osmangazi University Faculty of Economics and Administrative Sciences students by adopting the SERVQUAL measurement method. 'Bank customers' satisfaction' survey form as a data collection tool was used for examining the satisfaction of their banks [19]. This survey was conducted with 441 respondents by employing quinary likert style scale (1- Absolutely disagree, 2- Disagree, 3- Partly agree/disagree, 4- Agree, 5- Absolutely agree) [1].

2.1. Research Model and Hypotheses

The service quality of the banks, which is one of the most important institutions in the service sector, is very significant. In the banking sector, service quality is associated with customer satisfaction. There are many studies in the literature in which classical SEM analysis is applied to the quality of banking services [20-22]. SERVQUAL (Service Quality Measurement) model was preferred in the study in order to contribute to the literature performed with classical SEM and to point out the differences of BSEM. In the model provided by Figure 1 below, the dimensions of service quality, which measures satisfaction with banking services: A (Assurance); B (Responsiveness); C (Reliability); D (Tangible); E (ATM service); F (Accessibility); M (Satisfaction) [1].
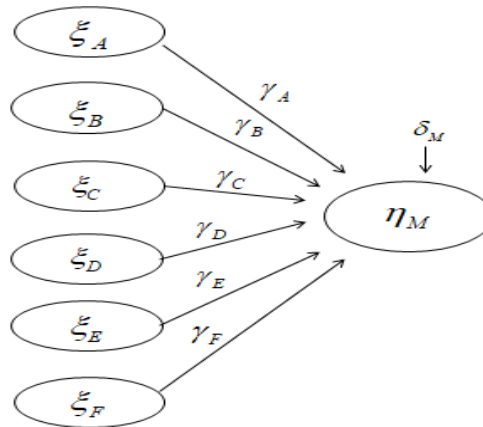

Figure 1. Research model

H_A: As the trust to the bank increases, the satisfaction of the customers increases.
H_B: As the enthusiasm of the banks regarding their services increases, the satisfaction of the customers increases.
H_C: As the reliability to the Bank's services increases, the satisfaction of the customers increases.
H_D: As the physical characteristics and appearance of the bank increase, the satisfaction of the customers increases.
H_E: As the ATM services offered by the Bank increase, the satisfaction of the customers increases.
H_F: As accessibility to the bank increases, the satisfaction of the customers increases.

2.2. Classical SEM

Classical SEM, also called LISREL, is formed of two main components: measurement model and structural model. Latent variables are estimated and evaluated with the help of observed variables and the relationships between these variables are shown in this measurement model.

A constructive model is formed with Path Analysis by the confirmatory factor analysis (CFA) [23, 24]. In classical SEM, assumptions are checked for parameter estimation and the methods of Maximum Likelihood (ML) and Least Squares Regression (LSR) method algorithms are generally used. This study adopted ML estimation method by postulating the required assumptions were provided. The general SEM definition showing the relationships between defined latent variables is given in Equation (1)

$$\eta = \Pi\eta + \Gamma\xi + \delta .\tag{1}$$

In Equation (1); η: q1 x 1 is a dimensional endogenous latent variables vector; ξ: q2 x 1 is a dimensional exogenous latent variables vector; Π: q1 x q1 is a dimensional endogenous latent variable showing the effect of structural parameter (correlation coefficients) matrix; The regression coefficients matrix having Γ (γ1, γ2): q1 x q2 dimension and showing the causality relationship between η and ξ; and also, δ: q1 x 1 is an error vector of endogenous latent variables.

Here, the error term δ of the endogenous latent variable is unrelated to the error terms of the observed variables and the exogenous latent variable. At the same time, the expected value of the error terms is 0 and the variance is constant.

Here, the error terms of the observed variables of the exogenous latent variable are unrelated to the endogenous and exogenous latent variables and the error term δ of the endogenous latent variable. Similarly, the error terms of the observed variables of the endogenous latent variable are unrelated to the endogenous and exogenous latent variables and the error term δ of the endogenous latent variable. At the same time, the expected value of the error terms is 0 and the variance is constant.

As for the measurement model, $y = (x_1^T, x_2^T)^T = (y_1, ..., y_n)$ observed data matrix, $\omega = (\eta^T, \xi^T)^T$ latent variable vector and $\varepsilon = (\varepsilon_1^T, \varepsilon_2^T)^T$ in for, the general expression of the measurement model is as in Equation (2)

$$y = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} \Lambda_1 & 0 \\ 0 & \Lambda_2 \end{pmatrix} \begin{pmatrix} \eta \\ \xi \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix}$$

$$y = \Lambda\omega + \varepsilon .$$

$$(2)$$

In the measurement model, ε_1 and ε_2 are unrelated to η, ξ and δ. Moreover, it is assumed that $E(\eta) = 0, E(\xi) = 0, E(\delta) = 0, E(\varepsilon) = 0$ [24]. $I - \Pi$, is a nonsingular matrix unrelated to ξ and δ.

$\Phi, \Psi_\delta, \Psi_{\varepsilon_1}$ ve Ψ_{ε_2} being the covariance matrix of $\xi, \delta, \varepsilon_1$ and ε_2 respectively, the covariance matrix of (x_1^T, x_2^T) is expressed as in Equation (3)

$$\sum = \begin{bmatrix} \Lambda_1(I-\Pi)^{-1}\left(\Gamma\Phi\Gamma^T + \Psi_\delta\right)(I-\Pi)^{-T}\Lambda_1^T + \Psi_{\varepsilon_1} & \Lambda_1(I-\Pi)^{-1}\Gamma\Phi\,\Lambda_2^T \\ \\ \Lambda_2\Phi\Gamma^T(I-\Pi)^{-T}\Lambda_1^T & \Lambda_2\Phi\Lambda_2^T + \Psi_{\varepsilon_2} \end{bmatrix} .$$

$$(3)$$

The SERVQUAL Model proposed in this study consists of an internal latent variable (M and q1 = 1) and three external latent variables (A, D, F and q2 = 3). In this model, the total number of observed variables for internal latent variables (M1, M2, M3) is three (r = 3) while the total number of observed variables for external latent variables (A1, A2, A3, D1, D2, D3, F1, F2, F3) is nine (s = 9). The matrix representation of the structural model proposed in the study is given in Equations (4)- (6), respectively

$$[\eta_M] = [0][\eta_M] + [\gamma_{MA} \quad \gamma_{MD} \quad \gamma_{MF}] \begin{bmatrix} \xi_A \\ \xi_D \\ \xi_F \end{bmatrix} + [\delta_M]$$

$$(4)$$

$$\begin{bmatrix} x_{1M1} \\ x_{1M2} \\ x_{1M3} \end{bmatrix} = \begin{bmatrix} \lambda_{M1} \\ \lambda_{M2} \\ \lambda_{M3} \end{bmatrix} [\eta_M] + \begin{bmatrix} \varepsilon_{M1} \\ \varepsilon_{M2} \\ \varepsilon_{M3} \end{bmatrix}$$

$$(5)$$

$$
\begin{bmatrix} x_{2A1} \\ x_{2A2} \\ x_{2D3} \\ x_{2A1} \\ x_{2D2} \\ x_{2D3} \\ x_{2F1} \\ x_{2F2} \\ x_{2F3} \end{bmatrix} = \begin{bmatrix} \lambda_{A1} & 0 & 0 \\ \lambda_{A2} & 0 & 0 \\ \lambda_{A3} & 0 & 0 \\ 0 & \lambda_{D1} & 0 \\ 0 & \lambda_{D2} & 0 \\ 0 & \lambda_{D3} & 0 \\ 0 & 0 & \lambda_{F1} \\ 0 & 0 & \lambda_{F2} \\ 0 & 0 & \lambda_{F3} \end{bmatrix} \begin{bmatrix} \xi_A \\ \xi_D \\ \xi_F \end{bmatrix} + \begin{bmatrix} \varepsilon_{A1} \\ \varepsilon_{A2} \\ \varepsilon_{D3} \\ \varepsilon_{A1} \\ \varepsilon_{D2} \\ \varepsilon_{D3} \\ \varepsilon_{F1} \\ \varepsilon_{F2} \\ \varepsilon_{F3} \end{bmatrix}. \tag{6}
$$

2.3. Threshold Value Approach for Ordered Categorical Data

The approach that provides more appropriate results for the evaluation of ordered categorical data is to define a threshold value to accept these data as latent continuous variables from the normal distribution. This approach accepts discrete categorical data (y) as a normal variable. y does not have precise continuous measurements. However, they are related to the observed ordered categorical variable z [25, 26]. This relationship is expressed as in Equation (7) below:

$$
\alpha_{k-1} < \alpha < \alpha_k \quad if \quad z = k, \quad k = 1, 2, 3, 4. \tag{7}
$$

In Equation (7), the number of categories associated with k, z; α_{k-1} and α_k represent the thresholds associated with y.

$-\infty < \alpha_1 < \alpha_2 < \alpha_3 < \infty$ where α_1, α_2 *and* α_3 are the threshold values. Sequential categorical data of the threshold value indication for Z is given in Equation (8) below:

$$
\alpha_k = \Phi^{-1}\left(\sum_{r=1}^{k} \frac{N_r}{N} \right), \quad k = level \ number. \tag{8}
$$

In the Equation (8), the term of Φ^{-1} is the inverse of the cumulative distribution function of the standard normal distribution N [0,1], Nr is the number of cases in the category r and N is the number of total cases. In this case, it is assumed that y is normally distributed. In this way, multivariate normal distribution of $Y = (y_1, y_2, ..., y_n)$ will be obtained [27].

2.4. Bayesian Structural Equation Modelling

The aim of BSEM is to make an analysis, which reflects the theories and prior knowledge better. This analysis is performed with the help of MCMC algorithms. In Bayesian estimation, posterior analysis is estimated, while structural parameters, latent variables, and sequence of threshold observations are simulated from the posterior distribution using the Gibbs sampler algorithm using MCMC methods. Under Bayesian approach in SEM, let $X = (x_1, x_2, ..., x_n)$ and $Z = (z_1, z_2, ..., z_n)$; be the observed continuous and ordered categorical data matrices, respectively; and let $Y = (y_1, y_2, ..., y_n)$ and $\Omega = (\omega_1, \omega_2, ..., \omega_n)$ be the matrices of latent continuous measurements and latent variables, respectively. In the Bayesian approach, the main purpose of addressing ordered categorical variables is to treat latent continuous measurements as missing data (Y, Ω) and to strengthen them with the data observed in posterior analysis [X, Z] as emphasized in the study.

Using this data amplification strategy, the model based on the complete data set also has continuous variables for ordered categorical variables. The threshold value approach also allows for easy interpretation of the parameters and associates them with a common normal distribution. The structural parameter vector

θ and common Bayesian estimations of Ω, which contain unknown parameter vectors in unknown thresholds $\alpha = \alpha_1,...,\alpha_k$, Φ, Λ, Λ_ω, Ψ, δ and Ψ_ε will be obtained by Gibbs sampling method. Initial values start with $\alpha^{(0)}, \theta^{(0)}, \Omega^{(0)}$ and $Y^{(0)}$ and it continues until j. iteration. At the end of the cycle, samples are obtained by producing $\alpha^{(j+1)}, \theta^{(j+1)}, \Omega^{(j+1)}$ and $Y^{(j+1)}$ from the common posterior distribution [27].

3. THE RESEARCH FINDINGS AND DISCUSSION

Students involved in the survey are composed by 57,6% women and 42,4% men. 21,3% of students are studying at first class, 17,9% of them are at second class, 20,2% of them are at third class and the rest of them are at fourth class. Regarding their departments, 19,3% of students are from economics, 30,4% are from business administration, 21,8% are from finance, 16,1% are from international relations and 12,5% are from political sciences and public administration.

Structural model has been evaluated by the ML estimation method for approximating parameters. Compliance criteria are employed to assess model harmony. As a result of this, it is seen that the installed model is good fit by seeing that compliance criteria of the structural model 0.95≤NFI: 0.98 (good fit), 0.97≤CFI: 0.99 (good fit), 0.90≤GFI: 0.93 (reasonable fit), 0,90≤AGFI:0.91 (good fit), RMSEA: 0.046≤0.05 (good fit), X^2/sd: 1.92≤2.00 (good fit). Classical SEM results of the parameters in the research model are given in Table 1 for indicating the significance.

Table 1. *Parameter, Reliability and Validity Values Obtained from Classical SEM*

Factors	İtems	Standard Loadings	t-value	R^2	CA	CR	AVE
A	Ideal banks fix customer-related errors in a way that suits the customer. (A1).	0,75	16,78*	0,56	0,78	0,78	0,74
	Ideal banks solve bank-generated errors in accordance with the customer (A2).	0,77	17,45*	0,59			
	Ideal banks studiously maintain keeping tracks of their transactions (A3).	0,69	15,21*	0,48			
B	Ideal banks' employees are always willing to help the customer (B1).	0,70	15,37*	0,49	0,76	0,76	0,71
	Ideal banks' employees devote close attention to solve customers' problems (B2).	0,72	15,94*	0,52			
	Ideal banks' employees always take care of customer's demands (B3).	0,72	16,02*	0,52			
C	Ideal banks do not make mistakes in debts or overdrafts (C1).	0,66	14,16*	0,44	0,73	0,74	0,70
	Customers always feel safe in ideal banks (C2).	0,74	16,35*	0,55			
	Ideal banks fulfil their promises on time (C3).	0,69	15,01*	0,48			
D	Ideal banks use modern technologic devices (D1).	0,68	14,74*	0,46	0,75	0,75	0,71
	Ideal bank employees' clothing looks pleasing to the eye (D2).	0,71	15,54*	0,5			
	The working halls of the ideal banks please the eye in terms of the interior design (D3).	0,73	16,28*	0,53			
E	The ideal banks have sufficient number of ATMs (E1).	0,69	15,44*	0,48	0,80	0,80	0,76
	All transactions can be done easily in ATMs of ideal banks (E2).	0,79	18,62*	0,62			
	The ATMs of the ideal banks are located in the most convenient places (E3).	0,79	18,51*	0,62			
F	Ideal banks can easily be reached via phone or internet when a problem is occurred (F1).	0,76	17,81*	0,58	0,79	0,79	0,75
	Ideal banks are conveniently located (F2).	0,76	17,66*	0,58			

	Ideal banks can easily solve problems, which is taken via phone or internet (F3).	0,73	16,62*	0,53			
M	I am glad to work with my bank (M1).	0,82	19.57*	0,66			
	I feel happy when I use my bank's banking services (M2).	0,78	18.54*	0,62	0,85	0,85	0,81
	I have a good and positive impression of my bank (M3).	0,82	19.87*	0,68			

CA: Cronbach Alpha, CR: Composite Reliability, AVE: Average Variance Extracted, *p<0,05
A: Assurance; B: Responsiveness; C: Reliability; D: Tangible; E: ATM service; F: Accessibility; M: Satisfaction

**Table 2.** *Classical SEM Parameters Estimation Results*

Hypotheses	Standardized Parameter Estimates	t-value	Result
H_A: A → M	0.20	2.16*	Supported
H_B: B → M	-0.06	-0.42	Not supported
H_C: C → M	0.21	1.52	Not supported
H_D: D → M	0.31	2.41*	Supported
H_E: E → M	-0.25	-1.41	Not supported
H_F: F → M	0.40	2.20*	Supported
$M_{SEM} = 0.20\xi_A + 0.31\xi_D + 0.40\xi_F + 0.46 \ (R^2 = 0.54)$			

*p<0.05
A: Assurance; B: Responsiveness; C: Reliability; D: Tangible; E: ATM service; F: Accessibility; M: Satisfaction

When the Banking Service Quality Model is examined by using the ML estimation method according to Table 2, it is observed that H_B, H_C and H_E hypotheses are not supported, whereas H_A, H_D and H_F hypotheses are statistically supported at 5% significance level. In other words, it is seen that the latent variables of Assurance, Tangible and Accessibility positively affect the latent variable of Satisfaction. A one-unit increase in Banks' Assurance (A) service dimension increases satisfaction with the bank by 0.20 units, a one-unit increase in Tangible (D) service dimension increases satisfaction with the bank by 0.31 units, and a one-unit increase in Accessibility (F) service dimension increases satisfaction with the bank by 0.40 units.

In this part of the study, Markov chains were produced with the help of Gibbs sampler through using the OpenBUGS package program for the research model described in Figure 2.
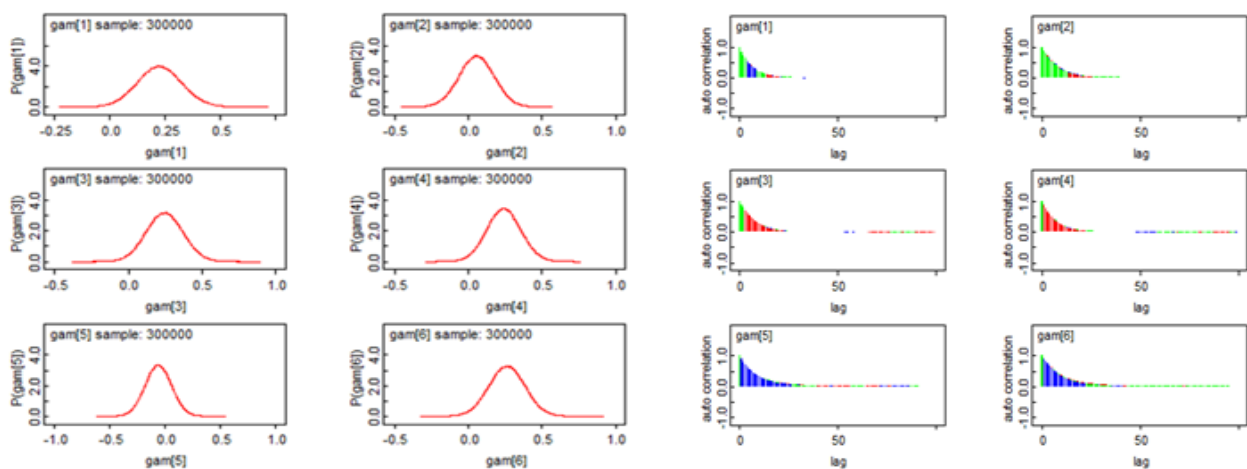
Figure 2. *The Symbolic Demonstration of Suggested System on OpenBUGS*

Three chains were used instead of a long single chain for the convergence values. The estimation values of the three chains used in tables and figures are given as average values instead of giving them separately. There are a total of 42 parameters in the model, including 18 factor loads, 18 error terms and 6 latent

variables. To reach convergence values for the model parameters, 100000 iterations were performed by the BSEM analysis. 300000 samples were formed over these three chains. The density and autocorrelation graphs of these three chains used for the parameters are given in Figure 3.
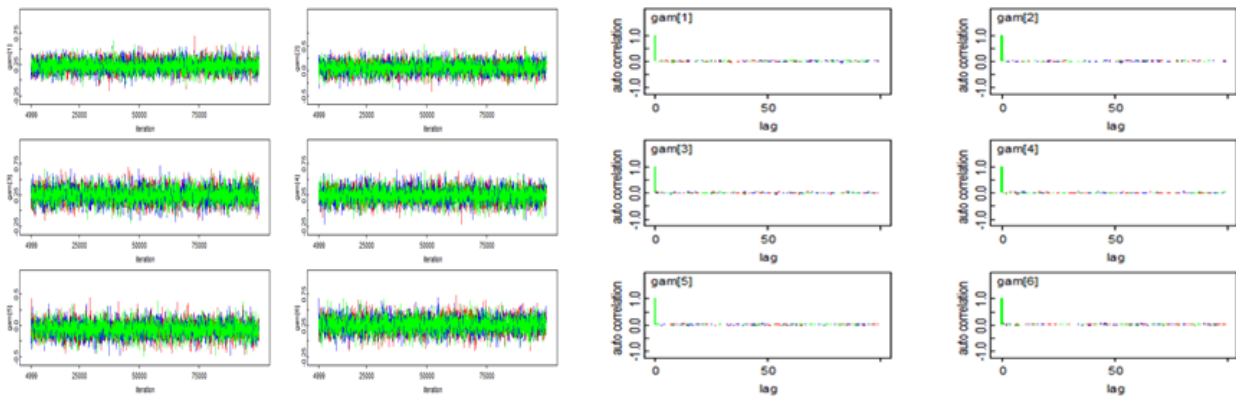

***Figure 3.** Density and Autocorrelation Graphics regarding Parameters*

When the density graphs in Figure 3 are examined, it is seen that the parameters provide normality assumption with 100 thousand iterations. To make accurate parameter estimation, independent observations must be provided. However, it is often difficult to obtain observations independently from MCMC in successive samples. In order to overcome this problem, attenuation https://tureng.com/tr/turkce-ingilizce/attenuation should be applied to the samples. The number of attenuation can be determined by determining the number of delays after autocorrelation. In the evaluation of the error values, densities, trace graphs and autocorrelation graphs of the parameters, thinning value is accepted as 40, burn-in period is taken as 5000 from the total of 7125 samples obtaining from 3 chains in the parameter estimation values are given in Table 3.

***Table 3.** Estimation Values of Parameters*

	mean	sd	MC_error	val2.5pc	median	val97.5pc	start	Sample
γ_1	0.2253	0.1017	1.12E-03	0.02901	0.2246	0.4229	5000	7125
γ_2	0.05494	0.1214	1.40E-03	-0.1812	0.05313	0.2913	5000	7125
γ_3	0.2467	0.1256	1.45E-03	0.001588	0.2455	0.4959	5000	7125
γ_4	0.2412	0.1171	1.40E-03	0.01141	0.2396	0.4751	5000	7125
γ_5	-0.06063	0.1209	1.29E-03	-0.2971	-0.06116	0.175	5000	7125
γ_6	0.2598	0.1234	1.39E-03	0.01858	0.2606	0.5032	5000	7125
λ_1	0.9138	0.05511	6.52E-04	0.8088	0.913	1.024	5000	7125
λ_2	0.9546	0.05629	6.65E-04	0.8488	0.953	1.068	5000	7125
λ_3	1.026	0.07046	8.69E-04	0.8956	1.024	1.169	5000	7125
λ_4	0.9482	0.07313	8.58E-04	0.8101	0.9462	1.098	5000	7125
λ_5	0.9869	0.07641	9.57E-04	0.8461	0.9853	1.144	5000	7125
λ_6	0.9934	0.07421	8.63E-04	0.8558	0.9914	1.144	5000	7125
λ_7	1.054	0.07892	1.01E-03	0.9069	1.052	1.217	5000	7125
λ_8	0.979	0.0795	1.03E-03	0.831	0.9766	1.144	5000	7125
λ_9	1.008	0.07776	8.48E-04	0.8651	1.006	1.168	5000	7125
λ_{10}	1.039	0.07995	9.48E-04	0.8899	1.036	1.208	5000	7125
λ_{11}	1.094	0.07205	8.19E-04	0.9563	1.091	1.24	5000	7125
λ_{12}	1.065	0.07267	8.85E-04	0.9258	1.064	1.211	5000	7125
λ_{13}	0.9621	0.06542	7.75E-04	0.8406	0.9599	1.098	5000	7125
λ_{14}	0.9406	0.06541	8.21E-04	0.8169	0.9389	1.073	5000	7125

When the Table 3 is examined, it is seen that the MC error value of the parameters is smaller than the standard deviation values in all parameter estimation values of the measurement model and SEM. According to the Thumb rule, the standard deviation of the Monte Carlo error value obtained from the Markov chain in the Bayesian approach is less than 5%, indicating that the convergence values are predicted with higher sensitivity. In addition, the MC error values indicate the values at which the convergence is achieved more clearly than the trace graphs or density graphs. However, since there is not a single

determination method to evaluate convergence, trace graphs and autocorrelations of the parameters are also examined. When Table 3 is examined, it is seen that gam (2) and gam (5) values, the values of Enthusiasm (B) and ATM (E) were not statistically significant; whereas the values of gam (1), gam (3), gam (4) and gam (6), namely, Assurance (A), Reliability (C), Physical Appearance (D) and Accessibility (F) latent variables respectively, were found to be statistically significant. Figure 4 verified the autocorrelation problem is corrected and the parameters converge.
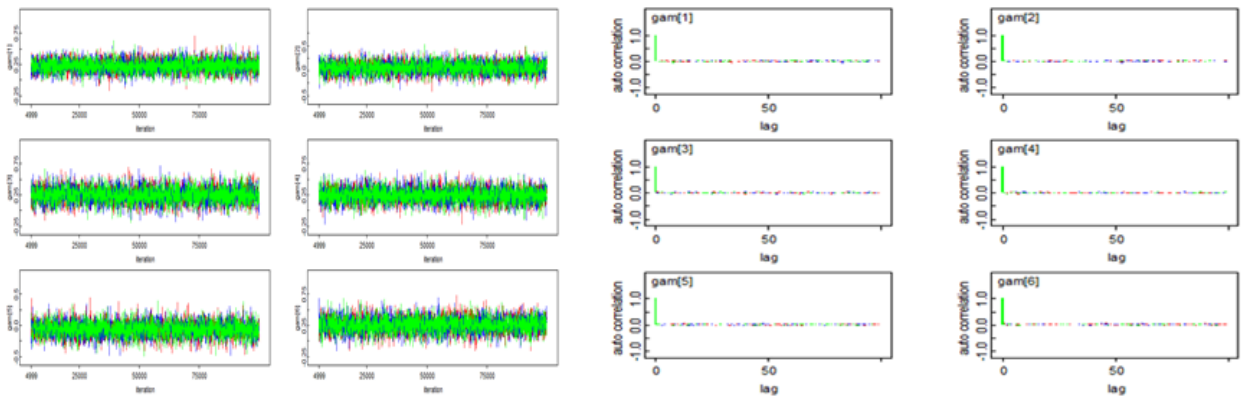

Figure 4. *Trace and Autocorrelation Graphs of Parameters After Burning Period*

4. RESULTS

In this study, classical SEM and BSEM parameter estimation methods were compared in terms of sequential categorical data. In the study, SERVQUAL model was accordingly chosen for measuring the satisfaction of banking service quality consisting 6 latent variables. The variables that affect the satisfaction of university students with the service quality of their banks are given in Figure 5 mentioned below.
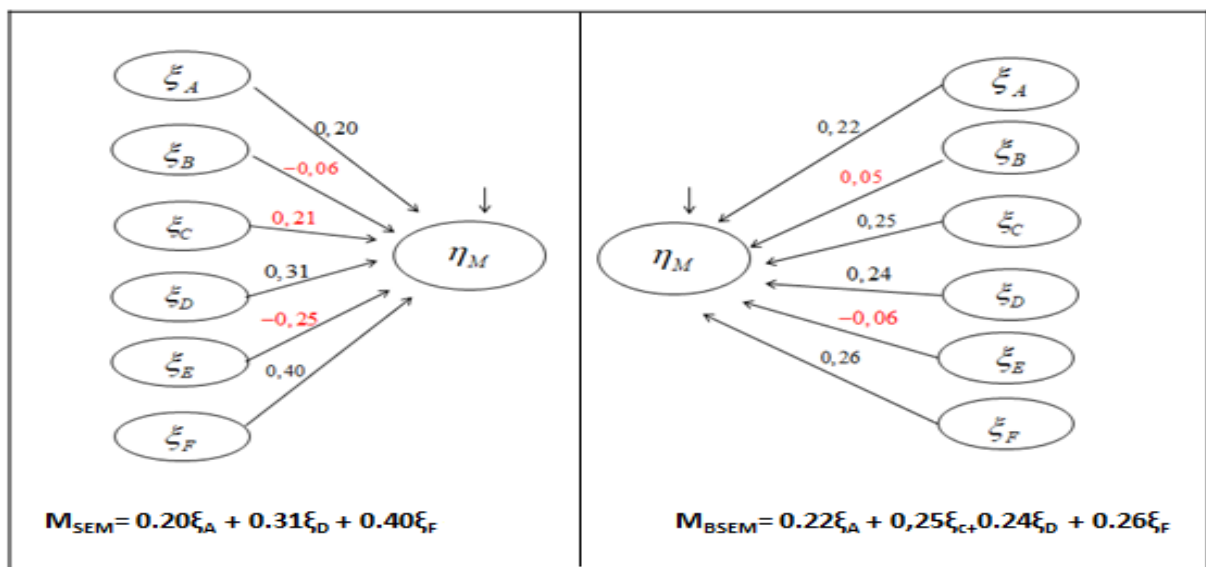

Figure 5. *Parameters estimation of classical SEM and BSEM*

When the comparison of parameter estimation results in Figure 5 is examined, it is concluded that the service dimensions, which affect students' satisfaction with banking services are Assurance (A), Physical Appearance (D) and Accessibility (F). Reliability (C) as a service dimension were also found statistically significant by employing the Bayesian estimation method as well as Assurance (A), Physical Appearance (D) and Accessibility (F).

When the parameter estimations are examined, it is seen that the service dimensions, which are significant in both methods, affect satisfaction in different amounts [1]. For example, Accessibility (F) service

dimension affects satisfaction by 0.40 units in classical SEM analysis, while it affects 0.26 units in BSEM analysis. Analyses found both SEM and BSEM estimation methods suitable. Nevertheless, as the error values of the parameters were higher in the SEM parameter estimation method, BSEM would be more accurate and compatible. It is thought that the application of the BSEM estimation method for the SERVQUAL service model, which had been studied many times through using the SEM estimation method, would probably contribute to the literature. BSEM provides several advantages for researchers in terms of saving both time and cost. It also provides the ability to work with a wide range of data types by dint of its flexible structure to use of prior knowledge. However, the lack of a definite rule in determining the convergence and burning period is a disadvantage of the traditional approach in SEM. The application of BSEM parameter estimation in sequential categorical data with smaller sample sizes would likely be useful in order to show the distinctive differences in future studies.

ACKNOWLEDGEMENT

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

REFERENCES

[1]   Erkan, G., "Comparison of parameter estimation in classic and bayesian structural equation models: an application with ordered categorical data", MSc. Thesis, Hacettepe University Graduate School of Science and Engineering, 1-70, (2019).

[2]   Palomo, J., Dunson, D. B., and Bollen, K., Bayesian Structural Equation Modelling, Handbook of Latent Variable and Related Models, Sik-Yum Lee, North-Holland, 163-188, (2007).

[3]   Yanaur, F., "The estimation process in bayesian structural equation modelling approach", Journal of Physics: Conference Series, 495(1): 12-47, (2014).

[4]   Lee, S. Y., Structural Equation Modeling: A Bayesian Approach, John Wiley and Sons, (2007).

[5]   Lee, S. Y., Song, X. Y., Basic And Advanced Bayesian Structural Equation Modeling: With Applications in the Medical and Behavioral Sciences, John Wiley and Sons, (2012).

[6]   Demeyer, S., Fischer, N., Saporta, G., "Contributions to bayesian structural equation modeling", 19th International Conference on Computational Statistics, Paris, 469-476, (2010).

[7]   Song, X. Y., Xia, Y. M., Pan, J. H., Lee, S. Y., "Model comparison of bayesian semiparametric and parametric structural equation models", Structural Equation Modeling, 18(1): 55-72, (2011).

[8]   Ozechowski, T. J., "Empirical bayes mcmc estimation for modeling treatment processes, mechanisms of change, and clinical outcomes in small samples", Journal of Consulting and Clinical Psychology, 82(5): 854-867, (2014).

[9]   Stenling, A., Ivarsson, A., Johnson, U., and Lindwall, M., "Bayesian structural equation modeling in sport and exercise psychology", Journal of Sport and Exercise Psychology, 37(4): 410-420, (2015).

[10]   Kim, J., Park, J., "Bayesian structural equation modeling for coastal management: the case of the saemangeum coast of korea for water quality improvements", Ocean and Coastal Management, 136: 120-132, (2017).

[11]   Harindranath, R. M., Jayanth, J., "Bayesian structural equation modelling tutorial for novice management researchers", Management Research Review, 41: 1254-1270, (2018).

[12]   Altındağ, İ., "Bayesian non linear structural equation model", PhD Thesis, Selçuk University, The Graduate School Of Natural And Applied Science, Konya, 1-141, (2015).

[13]   Lee, S. Y., Song, X. Y., "Evaluation of the bayesian and maximum likelihood approaches in analyzing structural equation models with small sample sizes", Multivariate Behavioral Research, 39(4): 653-686, (2004).

[14]   Rupp, A. A., Dey, D. K., Zumbo, B. D., "To bayes or not to bayes, from whether to when: applications of bayesian methodology to modeling", Structural Equation Modeling, 11(3): 424-451, (2004).

[15]   Kruschke, J. K., Aguinis, H., and Joo, H., "The time has come: bayesian methods for data analysis in the organizational sciences", Organizational Research Methods, 15(4): 722-752, (2012).

[16]   Palomo, J., Dunson, D. B., Bollen, K., Bayesian Structural Equation Modelling, Handbook of Latent Variable and Related Models, Sik-Yum Lee, North-Holland, 163-188, (2007).

[17]   Zyphur, M. J., Oswald, F. L., "Bayesian estimation and inference: a user's guide", Journal of Management, 41: 390-420, (2013).

[18]   Muthén, B., Asparouhov, T., "Bayesian structural equation modeling: a more flexible representation of substantive theory", Psychological Methods, 17(3): 313-335, (2012).

[19]   Yılmaz, V., Ari, E., Gürbüz, H., "Investigating the relationship between service quality dimensions, customer satisfaction and loyalty in turkish banking sector", International Journal of Bank Marketing, 36(3): 423-440, (2018).

[20]   Amin, M., Isa, Z., "An examination of the relationship between service quality perception and customer satisfaction", International Journal of Islamic and Middle Eastern Finance and Management, 1(3): 191-209, (2018).

[21]   Arasli, H., Katircioglu, S. T., Mehtap-Smadi, S., "A comparison of service quality in the banking industry", International Journal of Bank Marketing, 23(7): 508-526, (2005).

[22]   Caruana, A., "Service loyalty - the effects of service quality and the decreasing role of customer satisfaction", European Journal of Marketing, 36(7): 811-828, (2005).

[23]   Jöreskog, K. G., Sörbom, D., "PRELIS 2 User's Reference Guide: A Program for Multivariate Data Screening and Data Summarization: A Preprocessor for LISREL", Scientific Software International, (1996).

[24]   Jöreskog, K. G., "LISREL", Encyclopedia of Statistical Sciences, John Wiley and Sons, (2006).

[25]   Lee, S. Y., Song, X. Y., Skevington, S., Hao, Y. T., "Application of structural equation models to quality of life", Structural Equation Modeling, 12(3): 435-453, (2005).

[26]   Yanuar, F., Ibrahim, K., and Jemain, A. A., "Bayesian Structural equation modeling for the health index", Journal of Applied Statistics, 40(6): 1254-1269, (2013).

[27]   Lee, S. Y., Handbook of Latent Variable and Related Models, Elsevier, (2011).