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A Comparison of Structural Equation Modeling Approaches with DeLone & McLean's Model: A Case Study of Radio-Frequency Identification User Satisfaction in Malaysian University Libraries

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Abstract: This paper focuses on the application of mathematical theories in the study of information system (IS) success factors. The main objective is to apply Delone and McLean's IS success model for radio-frequency identification (RFID) sustainability in Malaysian university libraries. Two approaches are applied to estimate user satisfaction, such as the Bayesian and maximum likelihood estimation approaches. In order to identify the best approach, four mathematical indices are used, namely root mean squared error, absolute error, mean absolute percentage error, and the coefficient of determination. The results reveal that Bayesian estimation provides good fit to the data, unlike the model with the maximum likelihood estimator. This study addresses the causes for this difference between the two approaches, as well as the potential merits and shortcomings of the maximum likelihood approach. The current study presents a novel and practical modeling and prediction concept for researchers and experts in the field of computer science.

Keywords: Bayesian structural equation modeling; RFID; library user satisfaction

1. Introduction

A radio-frequency identification (RFID) system is a technology that identifies objects using radio waves of different frequencies [1]. RFID tagging of objects is the successor technology to barcodes, particularly in libraries. RFID is undeniably emerging at rapid speed, creating a space full of conjectures concerning the advantages that investments into it may have to offer [2]. Library management systems that entail RFI-related systems are known as well-established applications of this technology. Molnar and Wagner [3] argued that libraries are a hub for this rapidly developing RFID, as the technology sets the possibility to facilitate numerous library tasks to relieve repetitive strain injury of staff, allow rapid self-checkout for patrons, and make comprehensive inventory possible. The implementation of RFID in libraries can be traced back to the late 1990s [4]. According to the literature, RFID was first deployed in a library environment at the Singapore Public Library [5]. Since then, RFID has had an imperative role in the restructuring of library processes to make tasks easier for library staff and users in general. Due to its effective role in item identification and tracking, RFID technology is now adopted in various areas, including library management. Daily streams witness RFID support with avoiding thievery of goods, supply chain management [6], business campuses and airports [7], and even plant health monitoring [8], etc.

Although RFID-based systems provide a number of benefits such as cost savings, their implementation in organizational contexts has been slow for a number of reasons, including high implementation costs and integration problems [2]. Hence, the majority of early research works and industry efforts have concentrated on overcoming and understanding technological shortcomings. So far, very little scholarly attention has been directed to understanding the user or consumer perspective [4]. This was highlighted by a recent review on the topic by Irani, Gunasekaran [2], who debated that scholarly efforts should be made to investigate management and end-user-related issues that may be contributing to the failure of RFID implementation efforts. For instance, a few studies [9] from the retail domain have shown that staff/user resistance and the associated consumer apprehension to accept this technology effectively result in the failure of such implementation. It then becomes critical to scrutinize the factors affecting customer acceptance or rejection in other areas of RFID application including library management. Despite the fact that the two universally acknowledged advantages/benefits of RFID systems in the library context are patron self-checking and patron satisfaction, Kern [10], the literature discloses that extremely little effort has been invested to empirically examine these benefits. Current literature on technology adoption, for example Lee, Park [11] and Udo, Bagchi [12], indicates that to promote system usage, it is important to understand the factors that affect use and user satisfaction.

In light of the aforementioned facts, this study is intended to examine the factors that determine the usage and user satisfaction of RFID-based systems in libraries. The aim is achieved by undertaking an empirical examination of user perception with the aid of an online survey.

In libraries, regression [4] and structural equation modeling (SEM) are currently applied to estimate user satisfaction with RFID [13,14]. There are different SEM modeling estimation procedures, with the most frequently used being the maximum likelihood (ML) and partial least square (PLS) estimators. ML-based estimator analysis is likely to suffer from model misspecification due to the strictness of models with exact zero cross-loadings in addition to zero residual correlations. The PLS estimator for determining parameter estimates, is based on a kind of ordinary least squares regression. ML-based estimators can produce poor model fit [15] as well as extensive parameter bias in terms of factor loadings and correlations [16,17]. Strict model criteria are frequently refused [18], and researchers should make a series of modifications to models that may capitalize on chance [19]. Nonetheless, academic researchers who use ML intend to include several cross-loadings in addition to correlated residuals. ML-based estimation is not likely to explain all near-zeroes in cross-loadings and in correlated residuals that regularly exist in model measurement. Muthén and Asparouhov [18] developed a new Bayesian approach to assist researchers handle such problems. With this method, exact zeros are replaced with estimated zero informative priors in order to reflect fundamental theories appropriately.

In statistical modeling analysis, an informative prior of a variable determines specific and definite information about it. In applied research, informative priors can be categorized into three groups. (1) Prior distributions that provide numerical information vital for estimating the dependent variable in a model. This traditional informative prior would be derived from an earlier data analysis of the research or from the outputs of previous studies; (2) Prior distributions, in weakly informative prior status, are not able to support slightly controversial information. However, they are sufficiently robust to pull the data away from unfitting inferences, which are consistent with the likelihood status; (3) Uniform, or nearly uniform prior distributions essentially permit information prepared from the likelihood to be interpreted probabilistically. In this case, researchers call these non-informative priors. However, in some situations they have a weakly informative structure.

This Bayesian method facilitates the simultaneous estimation of all cross-loadings, as well as residual correlations in a particular model; however, if ML-based estimation is applied, simultaneous estimation is not possible [18]. In recent years, Bayesian SEM (BSEM) has been applied in different areas like engineering [20], psychology [21,22], and health [23,24].

Estimating the dependent variables in statistical modeling with a Bayesian approach is different than with maximum likelihood estimation. However, ML considers parameters as constants and works to recognize the estimates for certain parameters that present the best fitting models to the research data. In statistical modeling analysis based on Bayesian estimation, the process would entail the combination of data likelihoods and prior distributions to construct a posterior distribution. This combination leads researchers to apply Bayes' theorem to the estimation process. Bayes' theorem is a motivating tool that is behind modeling based on Bayesian estimators. Equation (1) represents the posterior distribution structure in the SEM context.

$$posterior = (parameters|data) = \frac{(data|parameters \times parameters)}{data} = \frac{likelihood \times prior}{data} \tag{1}$$

Each estimate obtained via the Bayesian approach is then a mean, mode, or median of the posterior distribution. An improvement of the Bayesian estimator over ML is that it permits research scholars to determine the prior distribution based on previous studies, thus decreasing the time consumed by the model to converge and producing more correct estimates [25]. Another improvement of the Bayesian estimator over ML is that the Bayesian approach does not perform the hypothesized asymptotic theory, meaning that large data are not essential to illustrate the effective statistical inferences [26]. The third improvement is that with a Bayesian estimator, better small-sample performance able be contained that infers no large sample theory is required. This point of view is demonstrated by the enhanced performance of small sample Bayesian factor analysis and better performance when a small number of clusters are analyzed with multilevel models. This, however, needs a careful optimal prior to distribution [18].

This paper aims to present Bayesian analysis and compare the BSEM with ML-based SEM approaches in terms of user satisfaction with library RFID. The Dwivedi, Kapoor [4] framework is employed to estimate user satisfaction with RFID in Malaysian public libraries.

The organization of this article is as follows. The two subsequent sections include reviews of Bayes' theorem and Bayesian estimation based on Markov chain Monte Carlo. Next, ML-based SEM and Bayesian estimators are compared. The fifth section presents the current study methodology. The sixth section provides the empirical findings and a discussion. The concluding remarks comprise part seven.

2. Bayes' Theorem

Each parameter in a Bayesian statistics model is presumed to have a distribution that drives with lack of certainty in relation to the parameter value [27]. This kind of distribution is usually explained before examining the data and it drives (un)certainty in relation to the parameters (step 1). This distribution-specified *a priori* is known as a prior distribution. In the subsequent step, the likelihood function of the data is generated by the observed data (step 2), and in the final step, the combination of the prior distribution with the data likelihood function produces a posterior distribution (step 3). Bayes' theorem is based on these three steps [28] and is formally written as:

$$p\ (\theta|y) = \frac{p(y|\theta).\ p(\theta)}{p(y)} \tag{2}$$

Bayesian statistics is based on this equation and demonstrates the difference between Bayesian and frequentist statistics [29,30]. Theoretically, the posterior likelihoods of the parameters provide the data, $p(\theta|y)$ remains equal to the likelihood, and $p(y|\theta)$, or the likelihood of data that provided the parameters is multiplied by the former likelihood of parameters, $p(\theta)$. Here, $p(y)$ stands for the marginal likelihood and the sum of all probable values of θ. However, $p(y)$ does not depend on θ; $p(y)$

is the marginal likelihood that acts as a normalizing factor (a constant) to ensure the likelihoods' sum is one [29]. Therefore, Bayes' theorem is commonly expressed as:

$$p(\theta|y) \propto p(y|\theta).\ p(\theta) \quad (3)$$

where $p(\theta|y)$ means that the posterior likelihoods are proportionate (i.e., $\propto$) to the probability of the data provided the parameters, $p(y|\theta)$, and is multiplied by the likelihood of the parameters, $p(\theta)$. The posterior likelihoods reveal the probability of all values of a parameter in θ given the data [31]. These parameter likelihoods are considered proportional to (a) the prior probability distribution $p(\theta)$ that stands for the likelihood of all parameters preceding any data collection (except empirical Bayes), and (b) the probability, or the likelihood of the data providing a variety of possible parameters, $p(y|\theta)$.

Bayes' theorem illustrates that by applying Bayesian analysis it is possible to find the model's posterior likelihood $p(\theta|y)$ given the perceived data and the prior. Contrary to traditional frequentist methods, the researcher is only provided the probability of observing the data assigned to the model $p(y|\theta)$. However, when employing Bayesian analysis, researchers are able to give likelihoods to set their model. In contrast, with frequentist methods, researchers assign likelihoods to their data given their theory or model, but no information is provided about the probability of the theory, model or hypothesis [31].

3. Bayesian Estimation: Markov Chain Monte Carlo

Bayesian statistics is extremely popular in the social sciences. This approach is recognized as the (re)discovery of numerical algorithms to estimate a model's posterior distribution of parameters assigned the data [29]. Markov chain simulation (also called Markov chain Monte Carlo (MCMC)) is identified as a general approach of representing samples from posterior distributions and reviewing the form of the distribution. In MCMC sampling, researchers derive the θ values from the estimated distributions, and these draws are subsequently modified to appropriately approximate the posterior distribution $p(\theta|y)$. Sampling in the MCMC approach is done in sequence, where every sample drawn is determined by the last value drawn and all draws collectively constitute a Markov chain [32]. The most vital element to MCMC success is improving the estimated distributions in every step of the simulation and uniting the target distribution.

The emphasis of frequentist methods regarding parameter estimation is on drawing the point parameter estimates using appropriate asymptotic attributes. ML is possibly selected because it is the most prevalent estimation method. Contrary to the ML estimation method, the focus of the Bayesian method in parameter estimation is on estimating the posterior distribution attributes; for instance point estimates and posterior likelihood intervals [29]. Brooks [33] presented a functional analogy to elucidate the distinction between the ML and Bayesian estimation methods using an MCMC algorithm. The MCMC algorithm is regarded as a discoverer for outlining an unexplored and intricate landscape. Such landscape represents the high-dimensional surface and likelihood distribution of interest (i.e., the posterior distribution). In addition, a discoverer aims to learn of the main landscape attributes. Due to the surface complexity, the discoverer is not able to scheme the entire route around the landscape; however, they are required to produce an appropriate path when walking, directed by prior distribution and the observed data, which act as the discoverer's compass. Thus, the landscape may serve as an appropriate metaphor [34,35] for the analysis of the likelihood distribution of interest, and the complexity of this landscape can be analyzed by means of algorithmic methods [36], or topological methods [37]. Similarly, the MCMC algorithm essentially travels the unexplored landscape surface to take numerous photos (i.e., samples) of the main attributes (i.e., parameter values). As the planning process continues, more information is combined in anticipation of a satisfactory resolution.

Conversely, the ML estimation method is likened to a mountain hiker that scales a complicated surface. The climber's aim is not to outline the whole surface, but rather to discover the maximum peaks, which are identified as a series of values to increase the probability of observing the data presented in the theoretical model (similar to the frequentist notion of the probability of data given the model [$p(y|\theta)$]). In the present position, the hiker discovers the surface aimed at a series of peak values surrounded by the whole parameter space and attempts to discover the sharpest uphill slope. A problem arising in this approach is that if the hiker begins on a lower mountain, he will rapidly climb to the summit but cannot arrive at other peaks that are higher than his existing position. This point is identified as being stuck in limited maxima and having the inability to discover the global or true maxima. While several improvements have been made to avoid the uphill-only rule, these improvements generally consist of making simpler hypotheses and estimates by assigning useful parameters to the surface complexity to assist the hiker with successful exploration. The MCMC explorer has the potential to successfully deal with these shortcomings using the ML estimation approach and is able to chart summits and valleys with complicated surfaces that are frequently encountered in SEM analyses.

To sum up, in an analysis to generate posterior distributions, samples of parameters that are symbols of the distributions are produced. In contrast, a Gibbs sampler is employed in BSEM as a substitute for ML estimation [38]. The Gibbs sampler is an MCMC algorithm used to attain a chain of observations that are estimated from a specific multivariate likelihood distribution [39]. The MCMC derives a vast sum of parameter samples from the posterior distribution and reviews the distribution created by the samples. These parameter values merge with the prior distribution, which, when mixed with the observed data, produce an illustration of the posterior distribution that serves to explain the posterior likelihood of, for instance, factor loading.

4. BSEM Model Assessment: Advantages over ML-Based SEM

Several benefits of the BSEM method have been proposed over ML-based SEM [38]. First, the Gibbs sampler offers better small-sample performance, since it is noted to be a reliable sampler for all numbers. Second, asymptotic inference is not required when operating BSEM, and as a result, normal approximations of the posterior do not exist. Consequently, the researcher is required to learn more about parameter estimates and model fit. The test statistics used for the observed data can be contrasted with statistics dependent on simulated data by drawing the parameter values from the posterior distribution. Moreover, compared to the application of estimated fit indices for assessing model fit using ML estimation that appears to function poorly in determining the severity of a model's misfit [40], in Bayesian analysis the researcher may employ posterior predictive distribution of p-values to assess the model fit [30,31]. The reason for checking the posterior predictive model, for instance the posterior predictive of the p-value, is to examine the simulated data produced by the model fit to the observed data [31,32,41].

The process of posterior predictive model checking is aimed at sampling posterior estimates of model parameters and utilizing these samples to produce a data series with similar size to the observed data set. The likelihoods of the observed and produced data sets are subsequently evaluated using chi-square values. The difference between two chi-square values is then calculated. The difference between chi-square values enables computing of a posterior predictive p-value and indicates the proportion of periods in which the observed data are more likely than the generated data. As this calculation is conducted on many MCMC restatements, it results in a difference in chi-square value distributions. If the difference is large, the model indicates poor fit, revealing that the observed or generated data have higher probability [31]. If the posterior predictive p-value is adjacent to 0.50, the observed data will be, on average, as probable as the generated data and indicate a good data-model fit. On the other hand, if the posterior predictive p-values are small (approaching 0.00), the observed data are unpredictable using the generated data, therefore suggesting data-model misfit [18]. It has been proposed that posterior predictive model checking (e.g., posterior predictive p-values) must be examined with bivariate scatterplots to find the inconsistencies [32].

Third, researchers can make less computationally challenging models. Model complexity leads to several dimensions of statistical integration when working with ML estimation, making it difficult or impossible to statistically estimate such models. Moreover, the posterior distribution of parameters in a recognized model can be found by employing the Gibbs sampler using an informative prior; conversely, using this sampler is not probable in ML-based estimation [31,38]. The fourth difference is the possibility to analyze new types of models. For instance, concerning the BSEM approach, the estimation of cross-loadings and residual correlations is possible in some recognized models. Particularly in Gibbs sampler analysis, the inclusion of informative or non-informative priors is possible [18]. For example, weak informative priors can be employed to change residual correlations and the exact zeros for the cross-loadings [42]. Applying this technique can resolve the problem of constraints in unrealistic models in terms of residual correlations and fixed cross-loadings that exist in "traditional" ML-based estimation [18]. Fifth, credible intervals can be potentially made for any parameter of concern. The confidence intervals in the frequentist approach are often misapprehended as indicative that the parameter of interest (e.g., regression coefficient, mean, variance) places in a particular interval, such as the 95% confidence interval [43]. However, the confidence interval in the frequentist method does not target an attribute of a particular parameter; rather, it reveals an attribute of the method. This method is based on the hypothesis that among a great number of recurring population samples, the true parameters of value arranged within the 95% confidence interval, the cases are under the null hypothesis [27]. Conversely, the confidence interval in the frequentist method does not refer to any information regarding the parameter of interest or particular confidence interval values; it only handles the procedure of drawing intervals in frequent use [43]. According to the Bayesian approach, the researcher can use credibility intervals to compute an interval that reveals the probability (e.g., 95%). Hence, the parameter of interest is situated between the two values provided by the observed data. This interpretation is more intuitive and meaningful and it is easier to convey than the frequentist confidence interval counterpart, since it makes the probability that a particular parameter places between two numbers [27]. Sixth, when a Bayesian approach like BSEM is adopted, the probabilities of the null and alternative hypotheses given the data are obtainable [44]. On the other hand, by using the frequentist *p*-value, the researcher is provided with probabilities of the alternative or null hypotheses assigned the data; this can be referred to as 'the probability of obtaining a value of test statistics, $D\ stand$, for large and more extreme than a value acquired conditionally on H_0 being true: $p(D|H_0)$" [45]. In terms of the difference between the Bayesian $p(\theta|y)$ and frequentist $p(y|\theta)\ appproach$, the researcher can utilize the accessible data and prior distribution by estimating the likelihoods of the assumptions or models. The methodology section presents a concise overview of the Bayesian model selection tools. Wagenmakers [44] offered explanatory reports on the critical distinction between the Bayesian and frequentist methods in terms of their capability to quantify statistical evidence.

5. Materials and Methods

The present research framework (Figure 1) and questionnaire were adopted from Dwivedi, Kapoor [4]. This framework was presented by Delone and McLean as the information system (IS) success model [46,47]. The questionnaire consists of two sections. The first section includes information related to (1) demographic characteristics, such as age, gender, and education level; (2) the rate of library visit recurrence; and (3) the degree of awareness of RFID technology. Students' responses were identified on a 5-point Likert-type scale as follows: 5 = strongly agree, 4 = agree, 3 = neither agree nor disagree, 2 = disagree, 1 = strongly disagree.

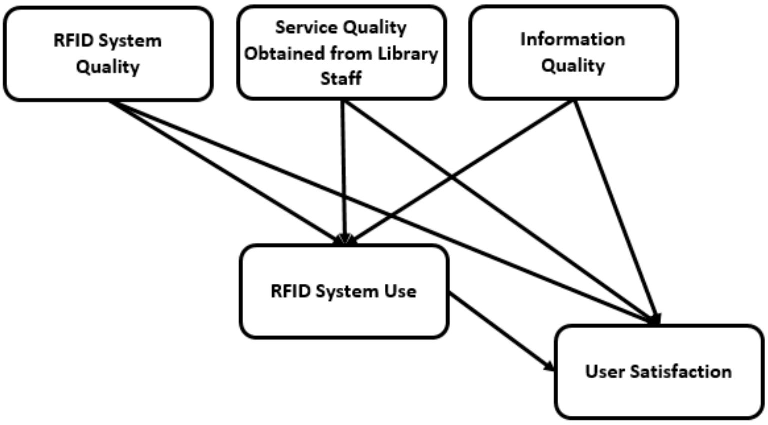

Figure 1. Research Model (source: Delone and McLean [46,47]).

Data were collected from student users at public university libraries, namely University of Malaya (UM), Universiti Kebangsaan Malaysia (UKM) and Universiti Purta Malaysia (UPM), who had applied RFID-based self-issue/return stations successfully. The questionnaire was distributed to 400 students who had been employing library services including regular book borrowing. The researchers discarded 36 incomplete questionnaires from the study to avoid missing data. Therefore, the number of cases considered was 364.

Two main statistical software were used for this research. For the first data analysis, AMOS version 18 software, based on the ML estimator, was used. AMOS is the most powerful statistical software among research scholars for estimating SEM approach modeling. This software is able to support the research hypotheses and theories by extending standard multivariate analysis techniques, containing correlation, analysis of variance, factor analysis, and regression. By applying AMOS, research scholars are able to design and implement frameworks even based on human behavior/attitude that reveal complicated relationships more accurately than standard multivariate statistics methods using either an intuitive graphical or programmatic user interface. Furthermore, to compare the ML-based method results, BSEM was employed with WinBUGS version 1.4. This software is a flexible statistical instrument used to investigate relationships regarding the violation of the standard assumption of variables studied in the model.

6. Empirical Findings

According to Fornell and Larcker [48], research reliability and validity are based on (a) validity—the Cronbach's alpha value of each construct should be equivalent to or higher than 0.7 [49], and (b) reliability—the average variance extracted should be equal to or greater than 0.50 [50]. As shown in Table 1, all Cronbach's Alpha and Average Variance Extracted (AVE) values meet the suggested norms and standards, subsequently indicating measurement model adequacy in terms of construct validity and reliability.

Table 1. AVE and Cronbach's Alpha values.

Latent Variables	AVE	Cronbach's Alpha
RFID System Quality	0.55	0.81
Service Quality	0.67	0.77
Information Quality	0.81	0.76
RFID System Use	0.66	0.72
User Satisfaction	0.63	0.78

The next level of analysis is model fitting. Table 2 indicates the model fitting results using the SEM and ML-based estimation methods. Model fitting normally indicates the degree of how well the designed model/framework reproduced the observed matrix of variances and covariances among a set of indicators or variables. Seven indices were considered for model fitting. The first and most important is the goodness-of-fit index (GFI). GFI is used to evaluate the discrepancy between the predicted or estimated covariances and resulting or observed ones. Equation (4) denotes the GFI equation. The acceptable GFI range is between 0 and 1, where 1 indicates a perfect fit and illustrates that measures equal to or larger than 0.90 signify a 'good' fit.

$$\mathrm{GFI} = 1 - \left[\frac{\max[(\chi^2 - df)/n, 0]}{\max[(\chi^2_{null} - df_{null})/n, 0]}\right] \tag{4}$$

Root mean square error of approximation (RMSEA) is the second index for model fitting analysis, which is presented in Equation (5). RMSEA serves to gauge the approximation error in the population. Here, RMSEA had a small value. Nearly 0.05 or below for RMSEA means a more suitable and nearer model fit in connection with the degrees of freedom. However, values between 0.05 and 0.08 indicate the most desirable standing and more optimal fit outcomes.

$$\mathrm{RMSEA} = \left[\frac{(\chi^2 - df)}{(n-1)df}\right]^{1/2} \tag{5}$$

The third index is the comparative fit index (CFI), which is calculated with Equation (6). This index is not only less affected by sample size, but is also based on comparing the hypothesized model to the null model. The value of CFI ranges between 0 and 1. However, the value needs to be a minimum of 0.90 to be suitable for model fit analysis.

$$\mathrm{CFI} = 1 - \left[\frac{\max[(\chi^2 - df), 0]}{\max[(\chi^2 - df), (\chi^2_{null} - df_{null}), 0]}\right] \tag{6}$$

The Tucker Lewis index (TLI) is the fourth model fit index and is presented in Equation (7). TLI is used to gauge parsimony, which is appropriate through the assessment and evaluation of the degrees of freedom of the suggested model to the degrees of freedom of the null model. Nevertheless, it is not certain whether TLI can vary from 0 to 1. A fit model must have a TLI larger than 0.90.

$$\mathrm{TLI} = \left[\chi^2/df_{(Null\ Model)}/\chi^2/df_{(Proposed\ Model)}\right]/\left[\chi^2/df_{(Null\ Model)} - 1\right] \tag{7}$$

The fifth index is the adjusted goodness-of-fit index (AGFI), which is shown in Equation (8). AGFI is utilized to adjust the GFI related to the model complexity. AGFI is measured between 0 and 1, where 1 or above (AGFI > 1.0) signifies a perfect fit. Nevertheless, it cannot be bounded below 0, i.e., AGFI < 0. As in the case of GFI, AGFI values equal to or bigger than 0.90 signify a 'good' fit.

$$\mathrm{AGFI} = 1 - \left[(1 - \mathrm{GFI})\frac{d_{null}}{d}\right] \tag{8}$$

The sixth index is the normed fit index (NFI). The structure of NFI is presented in Equation (9). NFI is applicable to contrasting and comparing the fit of a suggested model against a null model. This index defines all observed variables as uncorrelated. The values of NFI range between 0 and 1, where 0.90 signifies an optimal fit.

$$\mathrm{NFI} = \left[\chi^2/df_{(Null\ Model)}/\chi^2/df_{(Proposed\ Model)}\right]/\left[\chi^2/df_{(Null\ Model)}\right] \tag{9}$$

The NFI, CFI, GFI, and RMSEA values are not within acceptable limits. Thus, the research hypothesis is rejected and the present model does not fit the given data well at the 5% significance level.

Table 2. Model fit analysis.

Fit Index	Value	Critical (Acceptable) Value	Acceptability
NFI (Normed fit index)	0.825	>0.9	–
CFI (Comparative fit index)	0.857	>0.9	–
TLI (Tucker Lewis index)	0.916	>0.9	+
IFI (Incremental fit index)	0.945	>0.9	+
AGFI (Adjusted goodness-of-fit index)	0.968	>0.9	+
GFI (Goodness-of-fit index)	0.885	>0.9	–
RMSEA (Root mean square error of approximation)	0.189	<0.08	–

Figures 2–4 illustrate that the estimated structural equations handle the relationships between user satisfaction and RFID system quality, RFID system use, service quality from library staff, and information quality with the ML-based SEM, PLS-SEM, and BSEM methods.

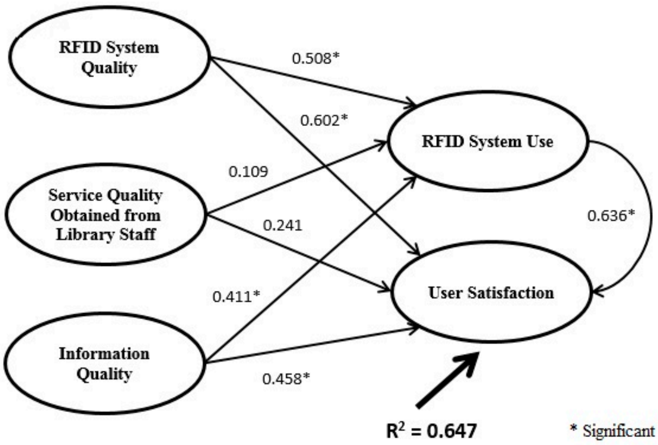

Figure 2. Research model results with maximum likelihood (ML)-based structural equation modeling (SEM).

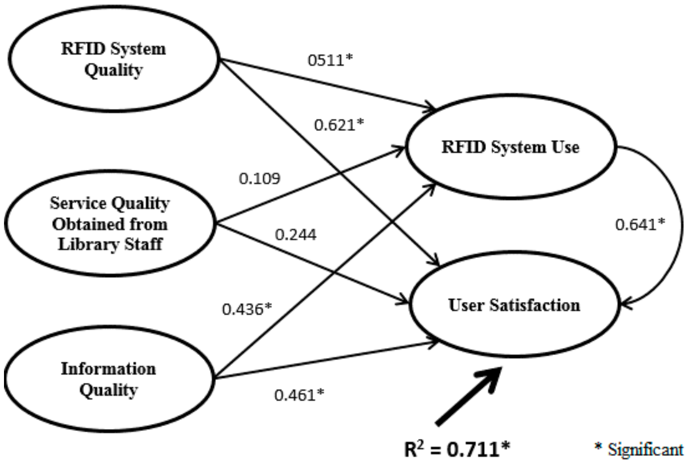

Figure 3. The outputs of research model based on partial least square (PLS)-SEM.

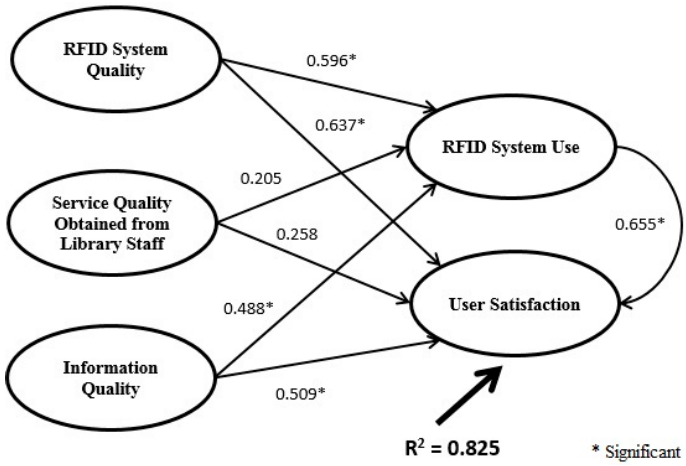

Figure 4. Research model results with Bayesian SEM (BSEM).

Applying the structural equations revealed that compared with the three other hidden variables, using the RFID system has the most significant effect on user satisfaction. There was a positive and significant relationship between RFID system quality and the user satisfaction index. It can be concluded that there was a significant correlation between RFID system quality and the library service condition, indicating that libraries with improved and maintained service quality lead to higher levels of user satisfaction. The findings from this study also revealed that information quality directly influenced the user satisfaction index, and that this relationship is significant. Moreover, it was found there was no relationship between service quality derived from library staff and RFID system use and the user satisfaction index.

In terms of Bayesian analysis, prior distribution was used to update the present information on the parameter. If no prior information is available, it is suggested to utilize non-informative prior information instead of imperfect subjective prior inputs [25]. However, because this study included a larger sample, the estimated parameters obtained appear to be less susceptible to the diverse alternatives of prior inputs. Consequently, the prior inputs should be selected carefully and cautiously when the sample size is small.

Finally, the BSEM outputs were compared with the ML-based SEM approach. Chatterjee [51] presented four indices, including mean absolute percentage error, root mean squared error, the coefficient of determination (R^2), and mean absolute error.

$$\text{Mean Absolute Error} = \frac{\sum_{i=1}^{n}\left|y_i' - y_i\right|}{n} \tag{10}$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(y_i' - \overline{y}_i'\right).\left(y_i - \overline{y}_i\right)\right]^2}{\sum_{i=1}^{n}\left(y_i' - \overline{y}_i'\right).\ \sum_{i=1}^{n}\left(y_i - \overline{y}_i\right)} \tag{11}$$

$$\text{Mean Absolute Percentage Error} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i' - y_i}{y_i}\right| \tag{12}$$

$$\text{Root Mean Squared Error} = \sqrt[2]{\frac{\sum_{i=1}^{n}\left(y_i' - y_i\right)^2}{n}}, \tag{13}$$

Here, y_i represents the ith real value of the dependent variable and y_i' is the ith predicted value. Table 3 illustrates the performance of the four indices above for the ML-based SEM and BSEM approaches.

Table 3. Comparison analysis of ML, PLS, Bayesian SEM outputs.

	Statistical Indices for Comparison Analysis			
	R^2	Mean Absolute Error	Mean Absolute Percentage Error	Root Mean Squared Error
SEM with Bayesian Estimator	0.827	0.241	0.021	0.049
SEM with PLS-based Estimator	0.711	0.325	0.036	0.063
SEM with ML-based Estimator	0.647	0.298	0.029	0.067

The four index structures were divided into two groups. One group of indices included mean absolute percentage error, root mean squared error, and mean absolute error, which are based on the error term $(y'_i - y_i)$. The other group included R^2 and were based on real and expected values.

R^2 is the most important indicator in all kinds of modeling regression, partial least squares regression and SEM (Bayesian or maximum likelihood). In statistics it is called the "coefficient of determination" and is equal to the Explained variation/Total variation. In other words, R^2 is the proportion of variance (%) in the dependent variable that can be explained by the independent variable/s. This value is a measure of the proposed model's fitness to the observed data in the context of regression analysis. SEM is shown in Figure 1 and the outputs of data analysis based on ML-SEM, PLS-SEM, and B-SEM are presented in Figures 2–4. The R^2 for B-SEM was 0.827, meaning that 82.7% of variation in user satisfaction (dependent variable) was related to RFID system quality, service quality, information quality, and RFID system use. The value of R^2 for PLS-SEM was 71.1%, and ML-SEM is equal to 64.7%. The R^2 of B-SEM was higher than ML-SEM and PLS-SEM, which means that the strength of the relationship between independent variables and the dependent variable in B-SEM was higher than in ML- SEM and PLS-SEM. As a result, R^2 was representative of model goodness-of-fit and it illustrated that our data was more fitting to B-SEM than to both ML-SEM and PLS-SEM.

The root mean squared error, mean absolute percentage error, and mean absolute error values for the B-SEM model (0.241; 0.021; 0.049) were less than for ML-SEM (0.298; 0.029; 0.067) and PLS-SEM (0.325; 0.036; 0.063). Consequently, it was more useful to use the B-SEM method to estimate the user satisfaction index than the ML-SEM and PLS-SEM.

7. Discussion

The major aim of this paper was to explain the capability of the ML-SEM, PLS-SEM, and B-SEM methods to evaluate user satisfaction with library radio-frequency identification (RFID) in line with Dwivedi, Kapoor [4] study. From a traditional perspective, ML-SEM and PLS-SEM models were employed to investigate the most proper number of hidden variables to explain the observed data. The main point of ML-SEM was to conduct a concurrent test to describe the relationship between observed and relevant underlying or hidden variables, as well as the association between underlying variables [52].

ML-SEM and PLS-SEM as a demonstrative parametric modeling procedure and B-SEM as an illustrative semi-parametric modeling procedure, were used to investigate and predict the user satisfaction index. The B-SEM, ML-SEM, and PLS-SEM outputs are presented in Figures 2–4 and Table 3. For three models, all relationships among variables were significant except the impact of service quality on both RFID system use and user satisfaction. The R^2 value for B-SEM (82.7%) was higher than the both PLS-SEM (71.1%) and ML-SEM (64.7%) analyses.

The RFID system quality had the highest and most significant impact on RFID system use and user satisfaction compared with other relationships according to both models. A number of previous studies have illustrated the appropriateness of the system quality construct to explain use and user satisfaction regarding new technology, systems or applications; for instance, the RFID system for public libraries [4], the Greek Taxation Information System (measuring the success of the Greek taxation system), and knowledge management systems.

The significant influence of system quality on system use and user satisfaction was identified in 14 and 21 research studies by Petter and DeLone [53], respectively. Moreover, a meta-analysis of nine published research works indicates that both the use and user satisfaction constructs are strongly and significantly influenced by system quality [54]. Furthermore, the importance of system quality in promoting the utilization of RFID-based systems to users was highlighted and emphasized by Gunther and McGinity [55] and Günther and Spiekermann [56]. The present research outcomes (Figures 2 and 3) are in accordance with the majority of current studies on the IS success model and debates by RFID scholars that RFID-based system quality is a significant factor in defining system use and library user satisfaction.

The information quality construct along with system quality was deemed a main construct by the DeLone and McLean IS success model in both the 1993 and 2003 versions. The significance and usefulness of this construct in explaining use and user satisfaction have been tested and confirmed by a number of current research works. For instance, information quality successfully clarified the use and/or user satisfaction of ubiquitous computing [57], public education sector information systems [58], and healthcare system [59]. The important effect of information quality on system use, and significant positive effect of information quality on user satisfaction were identified by Petter and DeLone [53] in four and 15 study reports, respectively. Overall, the research finding analysis by Petter and DeLone [53] indicates that information quality has a significant and important effect on both use and user satisfaction constructs. In accordance with the above argument, the current research outcomes confirm the importance of information quality on determining system use and user satisfaction from RFID-based library system use.

Service quality as the third explanatory variable was introduced and presented in the 2003 version of DeLone and McLean's IS Success Model. Since then, its influence on use and user satisfaction have been tested empirically tested in a number of studies. However, most of these studies report that the service quality construct is ineffective in explaining system and user satisfaction [54]. Once again, the research outcomes regarding the service quality construct are in accordance with previous research findings.

Generally, an explanation for the underperformance of this construct may be hidden in the main reason for its creation. As indicated by Delone and McLean [46], the need to include the service quality construct was prompted by the changing IS function's role from providing information to providing service. However, it is debated that 'to measure the success of a single system, "information quality" and "system quality" may be the most important quality components' [46]. Moreover, in studying the overall IS department success, the service quality may be the most significant construct [46]. The majority of studies that employ the 2003 version of the IS success model have tested individual systems rather than overall IS department success, which may clarify its non-significance in a number of studies. Service quality is probably more effective when measuring web-based system success compared to individual systems such as RFID.

Lastly, RFID-based system usage in libraries has an important and considerable influence on user satisfaction. The results of this finding are in accordance with outcomes reported in previous studies [60,61] that indicated an important effect of system use on user satisfaction. Petter and McLean [54] conducted a meta-analysis of 26 studies and presumed that generally across all studies there is a weak but significant relationship between use and user satisfaction, as confirmed in the present research.

Based on the R^2, mean absolute percentage error, root mean squared error and mean absolute error indices, the Bayesian SEM model was more efficient in predicting user satisfaction with the data set gathered from public university libraries in Malaysia. The findings of this study revealed that RFID system use, information quality, and RFID quality significantly influence the user satisfaction index, but library staff service quality does not affect user satisfaction. These findings are consistent with the Dwivedi and Kapoor [4] study.

In terms of Bayesian approach estimation, Dunson [62], Scheines and Hoijtink [38], and Lee and Song [25] agreed that this technique can assist researchers to manipulate valid prior information and information available in the observed data. Therefore it is possible to produce enhanced outputs and provide useful statistics and indices, e.g., the mean and percentiles of the posterior distribution of unidentified parameters. The approach also yields more dependable results for smaller sample sizes. Lee's book, "Structural Equation Modeling: A Bayesian Approach" [63] lists a number of benefits of applying the Bayesian approach as follows:

- First, statistical techniques are superior in terms of the first moment attributes of individual raw observations that are simpler than the second moment attributes of the covariance matrix sample. Therefore, this approach is easier to apply in more complex circumstances.
- Second, this approach directly estimates latent variables and is considered superior to traditional regression methods.
- Third, this approach is not only for modeling to manifest latent variables directly through familiar regression functions, but it also provides more direct interpretations to conduct statistical analysis. Hence, it can be employed along with the most common regression modeling methods, such as residual and outlier analyses.

8. Conclusions

The current study suggests that the Bayesian approach is deemed a suitable structural equation model for analyzing user satisfaction with library RFID. In developing the ML-based SEM and the Bayesian method, attention was centered on random individual observations rather than the sample covariance matrix.

This study was aimed at investigating the degree of user satisfaction with RFID in libraries. Further studies are suggested on the function of BSEM for user satisfaction with other technologies in various industries, such as public health, banking, transportation, etc. It is recommended to apply both ML-based SEM as a parametric methodology and BSEM as a semi-parametric approach to compare neural networks (non-parametric method) with Bayesian structural equation modeling.

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