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Banking Service Loyalty Determination Through SEM Technique

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Abstract: This research work encompasses the modeling technique-Structural Equation Modeling (SEM), which is widely used in behavioral research. Structural Equation Modeling is capable of handling a large number of endogenous and exogenous variables that are latent. In this research work, Service Loyalty is taken as a latent variable that cannot be directly observed but needs to be specified through combinations of observed variables, like Attitude, Behavior or Conative components. The authors attempt to demonstrate (through Structural Equation Modeling) the Service Loyalty relationship with Service Quality and Service Satisfaction that is experienced by Bank Customers. This is expected to serve as a foundational research effort that supports further research on Service Loyalty.

Key words: Service loyalty, SEM, application

INTRODUCTION

Frequently, as researchers it becomes necessary that we have to relate two or more constructs and find the relationships among them. In this count the utility of Structural Equation Modeling (SEM) has become almost indispensable one. Ever since the publication of book by Joreskog and Sorbom in 1979 on advances in factor analysis and structural equation models, there has been a growing interest among the researchers in different disciplines to make use of SEM in their research work. Nonetheless, more than other disciplines, the amount of interest shown by researchers in management discipline in the application of SEM is a mammoth one.

In the pursuit of simultaneous analysis of relationships among several constructs in behavioral research, the sanctity of application of Structural Equation Model (SEM) is indisputable. Gone are the days where the complexity of application of this technique was considered high owing to the lack of availability of software, manuals and other literature. This trend is almost topsyturvied with volumes of books, articles and software becoming more affordable in recent years.

The intention of the present study is to provide an orientation to the researchers in the management related disciplines in the application of SEM analysis in their research work to enable them to keep pace with their counterparts in developed nations.

SERVICE LOYALTY IN BANK SETTING

Despite the extant literature on customer loyalty, it is recognized that the psychological processes behind customer loyalty are still ill understood. In today's highly competitive environment, organizations should protect the long-term interest of the customers and hence should seek the ways through which the customer loyalty toward the organizations will be forged. Marketers opine that these long-term relationships with the customers would enhance their profitability (Dick and Basu, 1994; Garbarino and Johnson, 1999; Grossman, 1998) increased sales, lower costs and other tangible benefits.

The time has come for the firms to consider this customer loyalty as a source of competitive advantage (Bharatwaj *et al*., 1993). It has been established that the customers will not be impressed by only the core product attributes as other firms are also providing similar offerings. The study of customer loyalty and business performance has been a focus in the customer relationship management (Reichheld and Sasser, 1990; Sheth and Parvatiyar, 1995).

While the study on brand loyalty has been the topic of research in the past, numerous research articles appearing in journals betokening the development and conceptualization of the service loyalty models. More than a dozen of articles have been published on customer loyalty in retail banking market (Beerli *et al*., 2002)

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alone as it has been recognized that many banks have introduced innovative products and service (Meiden, 1986) and that it is less expensive to retain a customer than acquiring a new one. The longer the customer stays with an organisation, the more positive outcome he generates which include increase in the value of purchase, increase in the number of purchases and the customers' better understanding of Organisational and vice-versa and more positive word-of-mouth (Trubick and Smith, 2000).

Several contributions have been made in service marketing literature in measuring the service loyalty (SERVLOYAL). Significantly, factors such as service quality (Caruana, 2002), service satisfaction, image (Mazursky and Jacoby, 1986; Osman, 1993), values (Andreassean and Lindestad, 1998), commitment (Dwyer *et al*., 1992) and trust (Luarn and Lin, 2003) are identified to have an impact on SERVLOYAL. Since service is peculiar that involves personal encounter and also has a bit of perceived risk in the consumption of the same (Crosby *et al*., 1990; Guiltinan, 1989) the measurement of loyalty has become a subject for discussion from a radically different perspective from that of a product loyalty. The term loyalty has been defined as a degree of continuity in patronage, customers' disposition in terms of preferences and intentions and a psychological process resulting in brand commitment.

Further, different measures of service loyalty have been utilized in different industries. While more number of articles on the measurement of servloyal is in extant for a retail banking service than for any other service sector, it was construed imperative by the authors to develop an all-encompassing measurement for servloyal in utilizing the various ingredients that would reflect the servloyal construct.

CONCEPTUALISATION

SERVLOYAL is conceptualized as an interaction of attitude and behaviour such that the behaviour (loyalty) is determined by the strength of relationship between relative attitude and repeat patronage. Extending this, the loyalty dimensions or concepts are to include behavioral, attitudinal and cognitive processes. The attitudinal dimensions of loyalty were to include attributes such as word-or-mouth, complaining behaviour and purchase intentions (De Ruyter *et al*., 1998).

The behavioral loyalty measures include attributes such as brand allegiance, price elasticity, share of category (number of times a brand is purchased in a given period) and price until switching (Rundle-Thiel and Mackay, 2001). The cognitive loyalty component includes attributes like preference to the service organisation, the belief that the service organisation provides best offer and suiting customer needs (Harris and Goode, 2004). But it should be mentioned that the loyalty dimension is to also include factors such as commitment and trust attributes, even though these constructs are often considered as antecedents to loyalty rather than components of loyalty.

Based on the review of the aforesaid earlier studies, the authors identified customer loyalty being expressed in terms of word-of-mouth, purchase intentions, price insensitivity and complaining in a bank setting. Using service loyalty as endogenous variable, an investigation is made to find out its relationship with the exogenous variables viz. service quality and service satisfaction.

SERVICE LOYALTY DETERMINATION USING SEM

For the purpose of the discussion, let us assume that the loyalty construct is described in terms of four variables, the values of which can be observed or measured directly.

In Fig. 1, the variables V_1, V_2, V_3 and V_4 are observed directly and measurable through administering questionnaire. These measured variables are also known as manifest variables or indicator variables. The latent variable 'loyalty (L)' is therefore inferred from the four measured variables. Latent variables are also known as constructs, factors, dimensions or unobserved variables. Extending the same example of service loyalty, suppose if it is required that we are to identify the relationship existing among the constructs such as service quality, service satisfaction and service loyalty (as frequently analyzed in the service marketing literature) for a typical retail banking services then the model would look like the one in Fig. 2.

The model shown in Fig. 2 involves analysis of three major aspects: firstly, the variables related with each of the constructs are to be confirmed that they do share variance or relationship with their respective constructs or latent factors. This involves the application of a special type of factor analysis namely, a Confirmatory Factor Analysis (CFA).

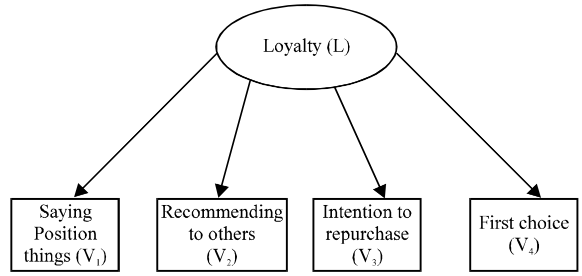
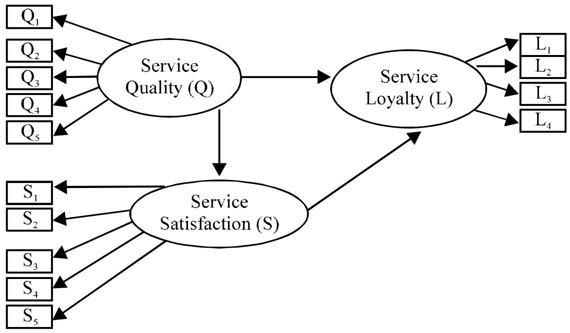


Fig. 1: Components of loyalty construct



Legend:

Q_1: Keeos promises
Q_2: Has customers' best interest at heart
Q_3: Always willing to help
Q_4: Gives personal attention
Q_5: Appealing physical facilities

S_1: Problem resolution
S_2: Employee attitude to the need
S_3: Transaction hours
S_4: Information provided
S_5: Processing time

L_1: Saying positive things
L_2: Recommending to others
L_3: Doing more business in future
L_4: First choice

Fig. 2: Relationships Among Service Quality, Service Satisfaction and Service Loyalty Constructs

Secondly, we find in the diagram (Fig. 2), the direction of the arrows moving from quality to satisfaction, quality to loyalty and satisfaction to loyalty. These arrows indicate the direction and amount of impact of one construct upon the other (i.e., the effect of quality on service satisfaction, quality on service loyalty and like that). These forms of directional relations are generally examined using either a path analysis or regression analysis. However, it should be noted that these path and regression analysis can be used for relating measured or indicator variables only and not the constructs. This is where SEM is considered important in analyzing the relationship among the constructs. Indeed, SEM is a combination of Factor Analysis, Regression Analysis and Path Analysis. Thus, SEM is a new approach to hypothesis testing when we have a number of constructs some of them which are simultaneously treated as both dependent and independent variables in the model (as in the case of Fig. 2, service satisfaction is a dependent (endogenous) latent variable while it is independent (exogenous) latent variable to service loyalty in the model). Overall, SEM enables us to test the hypothesized pattern of directional and non-directional linear relationships among a set of measured variables and latent variables in addition to providing the statistical indices for checking the fit of the model.

ADVANTAGES IN THE APPLICATION OF SEM

Even though SEM is a relatively new method, its application is enormous in the discipline of management. The use of SEM is rapidly accelerating due to the availability of user-friendly software such as LISREL (Linear Structural Relationship) and AMOS (Analysis of Moment Structure). Specifically, SEM has the following advantages.

- Greater flexibility in representing simultaneous analysis of relationship among theoretical constructs. For example, when the same construct happens to be both a predictor and a criterion (as in the service satisfaction [S] construct in Fig. 2;
- Collection of a set of manifest variables to represent a latent construct (as in the case of Fig. 2, where three sets of indicators are used to reflect each of the three constructs);
- Calculation of reliability of each of the latent construct in the model through the elimination of measurement error, which would bias the results;
- Provision for evaluation, confirmation, modification and comparisons of theoretical models;
- Visualization of a model by a graphical path diagram; and
- Evaluation of the overall model fit in addition to the assessment of strength of relationship among constructs.

DEMONSTRATION OF APPLICATION OF SEM

A SEM is divided into two parts viz., a measurement model and a structural model. The measurement model is used to specify the relationship between observed variables and latent variables. For illustration, based on Fig. 2, a simple measurement model for the three constructs would look like the one in Fig. 3.

As shown in Fig. 3, there are straight arrows from each of the latent constructs to their respective indicators. Each of the arrows from the construct to their observed variables will have a computed coefficient, namely a factor loading (similar to the loading in the exploratory factor analysis) which simply shows the amount of correlation or variance shared by the construct and the indicators.

However, it is a common practice in the measurement component of the SEM to fix one of the indicators (only one) to a value of one. This is technically required to give the construct an interpretable scale. The measurement model also includes an error component to each of the indicator variables. These errors are also known as measurement error factors or uniqueness. This is a distinct feature in SEM analysis as it also considers the error term in the model (it should be noted that neither regression analysis nor path analysis include the error component and to that extent their results are less reliable). Further, the errors or residuals of indicators can

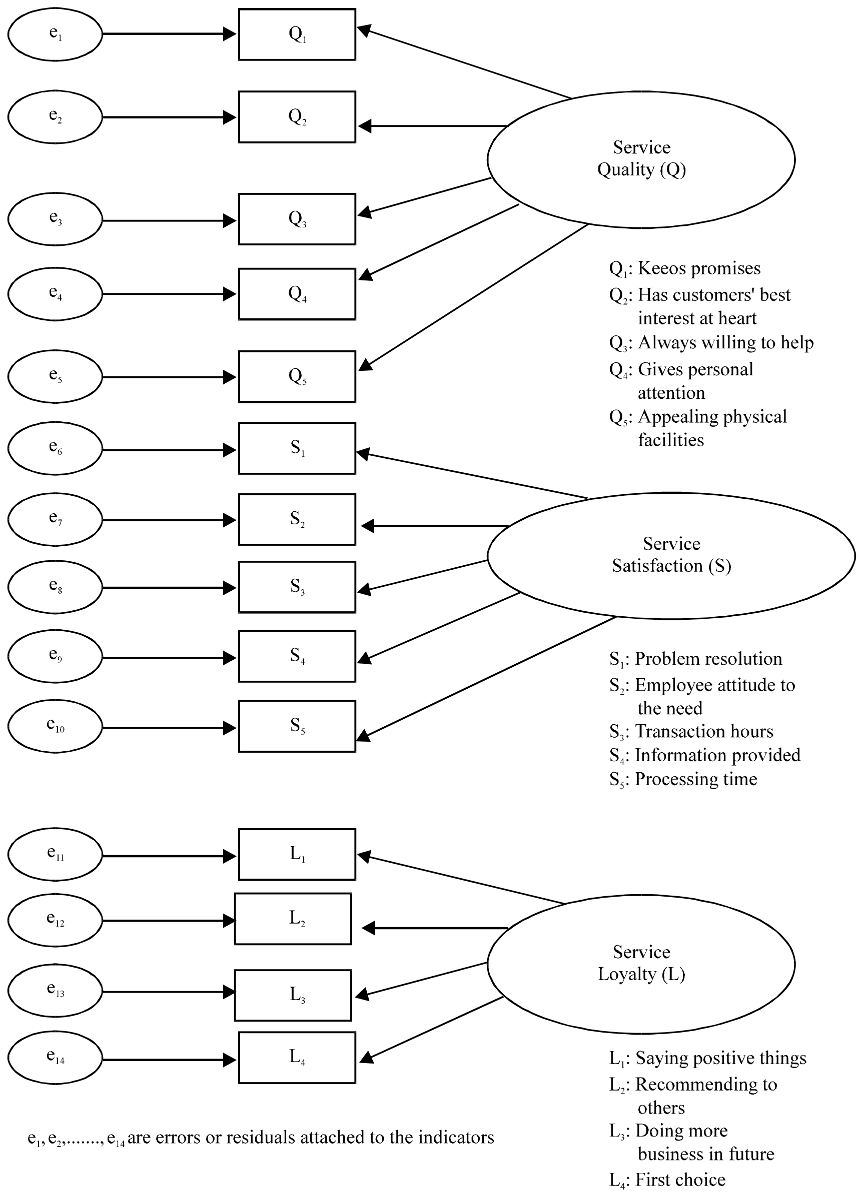


Fig. 3: Measurement Model for service quality, service satisfaction and service loyalty constructs

be correlated one another which can also be modeled in SEM. In the measurement model, a value of 1 should be obtained by squaring the corresponding factor loadings and similarly squaring uniqueness (error) i.e., (factor loading)^2 + (error)^2 = 1. Similarly, to find out the correlation between any two indicators, simply we need to multiply their respective path coefficient.

While the measurement model coins the indicators to their respective constructs, the structural model links constructs for the empirical test.

As described earlier, each endogenous latent variable (an endogenous latent variable or construct is the one with one or more arrows leading into it) is the criterion or dependent variable in the structural equation. For Fig. 2, three sets of equation will be developed: one, the path between service quality to loyalty; two, the path between service quality to service satisfaction and three, the path between service satisfaction to service loyalty. Thus three structural equations, one each for each path (or endogenous latent variable) are developed. Each structural equation would also include an error term. The impact of an exogenous construct on endogenous construct is measured in terms of standardized regression coefficient, also known as structural or path coefficients, mathematically, $\eta 1 = \gamma_{11}\xi_1 + \gamma_{21}\xi_2 + \delta_1$ where, $\eta 1$ = endogenous latent variable, γ_{11} = path coefficient, ξ_1 = exogenous construct and δ_1 = error in the measured variable.

SEM ASSUMPTIONS AND REQUIREMENTS

Like any other data analytical technique, SEM is no exception to assumptions. The major assumptions of SEM are:

- Level of measurement of indicator-all four levels of measurement (Nominal, ordinal, interval and ratio scaled) can be used;
- Either a variance-covariance or correlation date matrix derived from a set of observed or measured variables can be used. But a covariance matrix is preferred. In a nutshell,
  S = Σ, then model fits the data, where
  S = Empirical/observed/sample variance/covariance matrix
  Σ = Model implied variance/covariance matrix
  SEM deals with data in the variance-covariance matrix form as shown below.

	x_1	x_2	y
x_1	Var (x_1)		
x_2	Cov (x_1, x_2)	Var (x_2)	
y	Cov (x_1, y)	Cov (x_2, y)	Var (y)

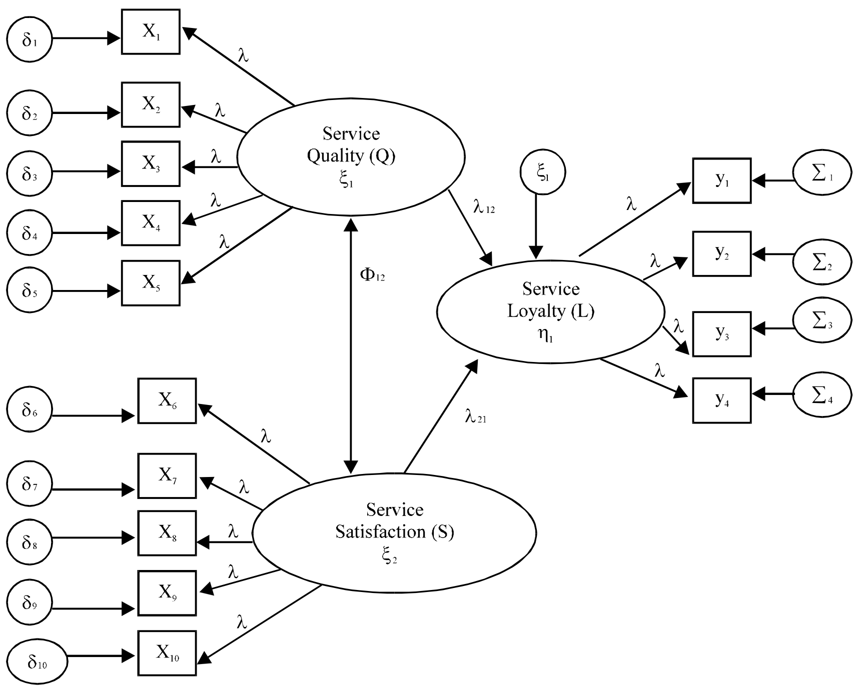
- In case correlation matrix is used, the following correlation coefficients are calculated:
  - Product-moment correlation-when both variables are interval
  - Phi-coefficient-when both variables are nominal
  - Tetrachoric coefficient-when both variables are dichotomous.
  - Polychoric coefficient-when both variables are ordinal
  - Point-biserial coefficient- when one variable is interval and the other is dichotomous
  - Poly-serial coefficient-when one variable is ordinal and the other is interval variable.
- Latent variables (constructs) are smaller that the number of indicators measured variables.
- Data are normally distributed: Here, the usual univariate normality checks are made by analyzing the skewness and kurtosis of each variable. In case of non-normality, one has to look for outliers and transformation of data. Tests such as Mardia-statistic can be used for checking the multivariate normality of all the variables considered together (Bentler and Wu, 1995). Also Satorra-Bentler statistic (Satorra and Bentler, 1988, 1994) or the use of item parcels (nothing but subscales in the scale) and transformation of non-normal variables (West *et al.*, 1995) can also be adopted.
- Linearity: SEM assumes a linear relationship among the indicators of measured variables. In case of non-linear relationships, Kenny-Judd (1984) Model can be endeavored. A detailed discussion of this is found by Jorekog and Yang's (1996).
- Sample size: A large sample size is required enenthough no consensus has been reached yet on this. For example, Ding *et al.* (1995) specify 100 to 150 respondents, while Boomsma (1987) indicates a minimum of 400. Bentler and Chou (1987) stipulate a ratio of 5 respondents per variable. However, it has been recommended here that any sample size of less than 150 may not produce reliable estimates. When evaluating models that are modified post-hoc, a much larger sample (800 or so) is required (MacCallum, 1986).
- Stochastic relationship between exogenous and endogenous latent variables. That is, not all of the variation in the dependent variable is accounted for by the independent latent variable (Kunnan, 1998).

DISCUSSION USING SEM PHASES

The SEM application involves five phases as stipulated by Bollen and Long (1993). These 5 steps are: Model specification, Model identification, Model estimation, Model testing and Model modification. A succinct of each of these phases is described here.

MODEL SPECIFICATION

In general, a SEM model is grounded in theoretical justification and includes two components, namely measurement model and structural model. The structural model phase requires us to coin linkages between latent variables (structural model), distinguishing between exogenous and endogenous latent variables and ensuring that no important latent variables is omitted, which will otherwise tantamount to a specification error (which is nothing but a lack of correspondence between the model under study and the true model in the population (Bagozzi, 1980). This stage also requires us to describe the measurement model, which specifies the relationships between measured variables and latent variables. The measured variables are also known as latent variable, which will have a set of multiple indicators (Howell, 1987). With regard to number of variables to be included in SEM model, it has been suggested that the SEM model should contain utmost 20 variables with 5 to 6 constructs, each measured by 3 to 4 variables. In order to understand the



Read,

δ = Delta (Error in measured value)
ξ = Zeta (Error in latent variable)
λ = Lambda (Path between indicator and construct)
η = Eta (Endogenous construct)
ξ = Ksi (Exogenous construct)
Σ = Psi (Error measurement)
Φ = Phi Correlation
γ = Gamma (Casual link coefficient)

Fig. 4: Path diagram for illustrative SEM model

model specification, we present a path diagram in Fig. 4. This path diagram is an extension of what was given in Fig. 2 but represented in a formal SEM notations and standard SEM construction rules.

The path diagram (Fig. 4) shows the illustrative model developed previously in the measurement of impact of service quality (Q) and service satisfaction (s) constructs on service loyalty (L) construct purely on Greek notation and model construction requirements for SEM. The path diagram specifies that the entire model is composed of two confirmatory models (one for latent exogenous constructs namely, Q and S and the other for endogenous construct, namely L). Both the exogenous constructs are linked to endogenous constructs by structural equation model: $\eta 1 = \gamma_{11}\xi_1 + \gamma_{21}\xi_2 + \delta_1$.

While in the measurement model, relationship can only be correlational, in a structural model relationships between latent constructs can be directional too. The parameters in the model can be either fixed or free parameters. Each parameter however represents relationship in a model. The fixed parameters are those that are not estimated from the data and are typically fixed at 1. The free parameters will vary depending upon the nature of relationship. In Fig. 4, we find the parameters x_1, x_6 and y_1 are fixed parameters and the loading of the measured variables on their respective latent constructs is fixed to 1. These fixed parameters are also known as reference indicators so that, the measurement scale for each latent construct can be set. The researcher should a priori specify the hypothesis about which pathways are important in the model.

MODEL IDENTIFICATION

The model identification concerns with the correspondence between the information to be estimated (i.e., free parameters) and the available information (the observed variance-covariance matrix). There are three possible model identification: A model is under-identified if one or more parameters are not estimable from the variance-covariance matrix; a model is just-identified if the number of parameters are estimable from the variance-covariance matrix and it is over-identified if there are many ways to estimate the parameter (Ullman, 1996). Usually, the model is over-identified for all SEM analysis. In Fig. 4, there are 14 indicator variables (5 each for Q and

S and 4 for L). Therefore, the number of elements = 1/2×14 (14 + 1) = 105. Therefore, degree of freedom = 73 (that is, 105 being the number of observed variances and covariances) -14 (being factor loadings) -14 (being residual variances) -1 (being correlation between Q and S) -2 (being a compact of Q on L and S on L) -1 (being residual variance for L). Hence the illustrated model is an over identified one and can be subjected for SEM analysis.

MODEL ESTIMATION

In this phase, decision is to be made as to how the parametric value is estimated. At any case, the parameter estimate should endeavor shrinking the discrepancies between the estimated and observed covariance matrix of the measured variables. Several estimation methods are available in any standard SEM software packages. Popular among them are Maximum Likelihood Estimate (MLE) and Generalized Likelihood Estimate (GLE). The MLE is generally considered good for sample size of any and is robust over GLE even if the multivariate normality is violated. MLE is also a relatively unbiased estimation of path estimates and is not dependent on scale of measurement. The only limitation of MLE is that it underestimates the standard errors associated with parameter estimates (Quintana and Maxwell, 1999). However, a number of substitutes to the MLE and GLE have been developed when there are serious departures from normality. Common among them are asymptotic distribution-free (ADF) method and Satorra-Bentler (S-B) correction procedure.

MODEL TESTING

Here, the model is subjected to fit, which is nothing but ensuring the closeness of observed and model estimated covariance matrices. This is done through computing the Global Fit Indices (GFI), which tell how well the SEM model fits the data. The most common GFIs are Chi-square statistic based on MLE, GLE, ADF and S-B estimation methods. Since the scientific hypothesis in SEM is that parameters are truly zero, we should fail to reject the null hypothesis, which indicates the adequacy of model to the observed data. This is paramount to be taken note of. The one limitation of using χ^2 as global fit index is it is inflated by a large sample size. Several alternative GFIs are available such as Root-Mean-Square-Error-of-Approximation (RMSEA) (Steiger and Lind, 1980), Comparative Fit Index (CFI) (Bentler, 1990), Root-Mean-Square-Residual (RMSR) (Hu and Bentler, 1995) and Goodness of Fit Index (GFI) developed by Joreskog and Sorebam (1988). While the values of GFI, CFI, are to be closer to a value of 1 for an acceptable fit of model to the observed data, the RMSEA, RMSR and χ^2 values are to be close to zero (Min and Mentzer, 2000, 2004). In regard to evaluating the individual parameters, care should be taken to ensure that the t-statistic for each path coefficient should be significant and the standardized residuals should not be greater than 0.03. As far as the latent variable is concerned, the R^2 value for each endogenous latent variable is to be large.

MODEL MODIFICATION

After the parameters are estimated for the specified model, the model may or may not have the required GFI indices. In cases where GFI indices are not at the recommended level, it would betoken that either the model is mis-specified or has produced biased parameter estimates. In such cases, instead of simply disbanding the model itself, it is better that an endeavor is made to re-specify the model. This involves searching a better fitting model from the estimation obtained in the originally rejected model. However, this new model developed so, should also be considered as tentative unless it is accepted using second model for verification (Diamantopoulos, 1994). The model modification or re-specification is done either by adding parameters, or eliminating non significant parameters whose t-values are non significant or by constraining a few parameters to zero. Nonetheless, it is reiterated that theoretical evidence for such addition or deletion of parameters exists. The effect of addition or deletion of parameter on the modified model can be found out by comparing the Chi-square value difference of unmodified model and the modified model for a one degree-of-freedom at 0.05 level of significance. Recent releases of SEM softwares make the model modification task much easier. The SEM output rank-orders listing of existing paths that may be considered for elimination so that the model fit can be improved. Importantly, extreme cautions should be exercised while taking the decision for model modification based on modification indices alone.

LIMITATIONS OF SEM APPLICATIONS

Even though SEM offers greater flexibility in representing a variety of theoretical models and relationships among constructs, it is not devoid of criticisms. The following major concerns related to SEM procedures are gleaned from the extant literature. Keeping them in mind will prevent the researcher or theorist in arriving at what is known as misleading observations,

- The use of SEM is problematic when attempted to interpret the results as evidence of the direction of causality. Despite the earlier name of casual model, SEM models cannot prove causation; the only thing SEM does is in extending the support whether the model does fit the observed data. Therefore, SEM is basically a model testing procedure instead of model building one.

- It is also difficult in knowing whether a model is complete or not if the literature is sparse in addressing equivalent or viable models. In simple words, creating an alterative model based on only the model modification-indices in SEM sans theoretical support from the literature for such modification will be a futile exercise.
- The lack of consensus over guidelines for acceptance of model) such as acceptable fit indices for both the overall model and individual parameters *per se*), requirement of large sample size for meaningful estimation of parameters and the multivariate normality assumptions prevent its universal application.

As a final note, it is underscored that the researcher should not plunge into the application of SEM for the research work unmindful of the aforesaid observations. Doing so would damage the latent model testing process.

CONCLUSIONS

In conclusion, the authors of this article have endeavored to orient the SEM concepts and application in marketing research with an illustrated focus on service quality-service satisfaction-service loyalty relationships in a bank setting (Israel and Clement, 2005). Aspects of SEM analysis, namely, establishing a structural model had been outlined in a step-by-step basis. While many more areas such as model validation, boot strapping, jackknife and multilevel models are important in completing the discussion on SEM.

It is the desire of the authors that research aspirant have woken up at least now to the use of this widely adopted sophisticated second generation analytical technique in their pursuit of model building and model testing tasks, like the relationship among the constructs, viz., service loyalty, service quality and service satisfication. Indeed, it is an enjoyable experience to accomplish this research task using numerous easy-to-operate software such as LISREL, AMOS are available at an affordable cost in this tech-savvy era. This research work endeavors to serve as a foundation for further research on model building and testing.

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