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MODELLING THE BRAND EQUITY USING STRUCTURAL EQUATION MODELLING

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Abstract

Modelling the Brand Equity is a must for any corporate. How much a brand is worth? Brands differ in their power and value in the market place. Brand Equity is the estimated value of premium customers are willing to pay for using a branded product compared to an unbranded product. Brand is an intangible assets and it is difficult to measure it directly. Brands, however, do not necessarily last forever. Hence it is important that they are monitored over a period of time.

Structural Equation Modelling methodology (SEM) provides a method to model brand equity that cannot be directly measured. In SEM terminology these are called latent variables. They are estimated using measured variables, or indicator variable(s).The measured variables need not be reliable and there will be a measurement error associated with each indicator variable. One latent variable can drive other latent variables and there can be two types of effects: Direct and indirect.

By using SEM with multiple indicator variables we can model important latent variables while also taking into account unreliability of measured variables.

This paper describes applying SEM to model the brand equity of Airlines. It also studies the comparison of SEM models across segments and identifies the most important variable(s) affecting the Brand equity. Primary data is used for analysis, collected among different dimensions covering demographic, satisfaction, commitment, Trust, Relation etc.

INTRODUCTION

As mentioned above Modelling Brand Equity and monitoring over a period of time is very important in the market place. It is a well-known fact that market

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place is competitive and does not remain stable over a period of time. Consequently Brand Equity which is the estimated value of premium customer is willing to pay also changes.

Since brand is a sort of perception plus many other things it cannot be directly measured. The Researcher thinks that by measuring certain variables we will be able to measure this. One may also think that other things which cannot be directly measured can also have an effect on Brand Equity.

SEM allows one to model such concepts, interaction among concept(s), and relation of concepts to measured variables, measuring the reliability of indicator variables to the concept modeled.

BRIEF OVERVIEW OF SEM

SEM supports two types of variables:

(i) Measured/Observed/Indicator

(ii) Latent

First category has numeric data, Responses to a Rating Scale in a questionnaire which can be ranked. Data cannot be categorical. The second category i.e. latent variables cannot be observed but we are interested to know about them. Latent Variables are modeled using observed variables. Examples of latent variables include Brand equity, perceived value, perceived quality, Customer satisfaction, Repurchase intention etc. In SEM terminology one uses "endogenous" for latent variables and "exogeneous" for measured/independent variables.

Model in SEM is shown in the form of a path diagram. Observed variables are drawn as rectangles; Latent variable(s) are drawn as circles. Errors that are estimated which are not directly measured are also shown as circles. When one variable is believed to cause another variable the relation is shown as directed arrow from cause to effect. This assumption is made by the modeler. One can also model correlation between variables which is shown as double headed arrow.

For each arrow there may be an estimated weight similar to co-efficient in regression. They are also called path co-efficient. Some times weights are constrained to a particular value. Normally a weight of 1.0 is specified for effect of error. This means that error is measured in same units of measurement scale of measured variable(s).

Latent variable(s) can be used as Dependent or independent variables. Normally Latent variable(s) are usually modeled using two or more observed variables.

As a simple example one wants to model Brand Loyalty as a Latent variable. You ask customers about use of brand, satisfaction, willingness to recommend to others. These become measured variables. You can use these responses on these measured variables to model loyalty as a Latent variable. Each indicator variable related to loyalty will have a path co-efficient.

There is an important difference between a similar technique called factor Analysis and SEM. Objective of Factor analysis is to be reduce a set of variables to a smaller number. In factor analysis the loading of any observed variables on any factor can assume any value i.e. no constraints are imposed. What is constrained is the number of Factors.

But in SEM the modeler/researcher specifies which path co-efficient are free and which are to be fixed. One can also specify whether the variables are independent or they co-vary.

Model fit

One arrives at a path diagram indicating the Latent Variables, Measured Variables, free parameters, constrained/fixed parameters and path indicating the Causation from Measured to Latent and among Latent Variables. The data is examined to see that they meet the distribution assumption. The path coefficients are estimated using maximum likelihood estimation which is a common method used. Normally overall model fit is evaluated using χ^2 fit statistics. The null hypothesis in SEM is model fits the data. Choose a confidence level say .05. If model χ^2 is greater than 0.05, the model is fine. If it is less than 0.05, the model does not fit the data.

There are various ways to improve the model. One method is to introduce additional constraints. This is done by looking at Modification Indices in the output. Choose the highest Modification indices and constrain these parameters. The fit will be better. One word of caution is that these constraints need to be introduced if it makes meaning in real sense.

Since χ^2 is sensitive to sample size, another ratio called "Discrepancy Ratio" is χ^2/df which is ratio of χ^2 to degrees of freedom is normally used to test the Goodness of Fit. This ratio should be around 1.5 for the model to be accepted.

There are a host of other Fit measures that are normally used to evaluate the goodness of fit. Most commonly used ones are Generalized fit Index, Comparative Fit Index, Tucker – Lewis Index and Adjusted Generalized Fit Index. Normally all these fit indices should be 0.9 and above for an acceptable Model.

Sometimes one has to compare SEM's across Segments. The usual method of doing this is Run SEM on one data set, Fit the model, and note the value of χ^2, path co-efficient. Now constrain the path Co-efficient for measured Variables to latent variables paths. The constrained model is also known as "Nested Model" as this has less degree of freedom compared to original model. Fit the model again. Note the value of χ^2. Compute the value of difference in χ^2 to the difference in degrees of freedom. This distribution is also χ^2. If this is significant at a given Confidence level (0.05) then the two models differ. We can also see the change in other path Coefficients.

BENEFITS OF USING SEM

- Latent variables or unobserved variables which measures a concept that cannot be reliably measured can be modeled using measured or observed variables and one can validate to the extent the concept is captured using measured variables.
- One latent variable can drive another latent variable.
- Direct and Indirect effects in path diagram can be explicitly analyzed.
- Correlation among independent variables can be taken into account.
- Errors or reliability of each measured variable(s) & also latent variable(s) can be analyzed.

These are some of the benefits of SEM compared to Standard Multiple Regression.

APPLICATION OF SEM FOR MODELING BRAND EQUITY FOR AIRLINES

The objective of the study is to model the Brand Loyalty using Airlines data. The hypothesized model is as follows. Brand loyalty is a latent variable. The Brand Loyalty in turn depends upon Trust and Commitment, which are also latent variables. Trust drives Brand Loyalty directly; Trust drives commitment directly and commitment in turn drives Brand Loyalty. Put alternatively, Brand Loyalty is directly related to Trust; there is also an indirect path to Brand Loyalty through Trust->commitment.

Trust in turn which is a latent variable is measured by the following three indicator variables. All indicator variables are measured on a five point scale.

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

Trust 2	Company is responsible
Trust 3	Company is reliable
Trust 4	Company is honest

Brand Loyalty Latent Variable commitment is measured by the following three Indicator Variables

AFF COMM1:	I feel like part of a family as customer of X
AFF COMM2:	I feel emotionally attached to X
AFFCOMM4:	I feel a strong sense of identification with X.

Brand Loyalty apart from being driven by Trust and Commitment, is also directly related to the following measured variables.

LONGEXP1:	I will continue to use services of X
SAT3:	Overall, I am satisfied with the decision to use – X
RS3:	You like recommending X to others seeking your advice.

Apart from the above measured variable the following information is also collected:

Gender, Occupation, Frequency of travel in a year, Class of Travel, Purpose of Travel, Member of Frequent Flier Program and Airlines.

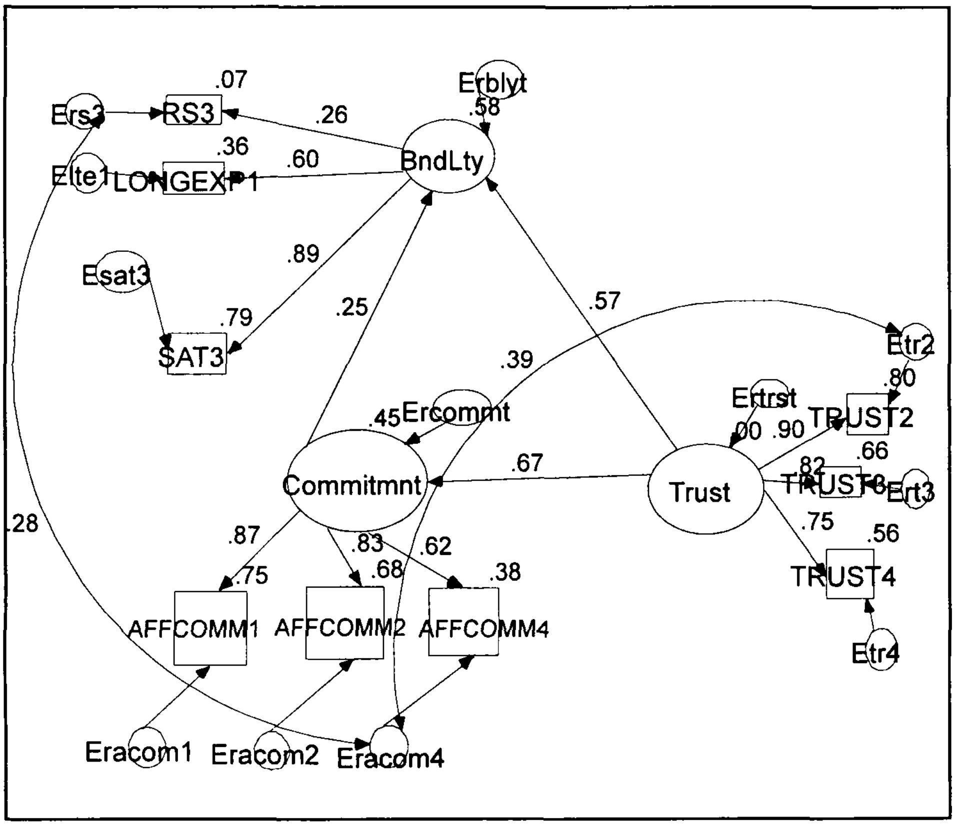

Figure 1: The path diagram

A sample of 295 Responses was collected for the Analysis from the THREE Airlines. Outliners were removed using the Mahalanobis distance method. There were 287 samples left after removal of outlier.

For Comparison of Brand Loyalty we segmented the data using Frequent Flier (FF) Membership as Segmentation variable. There were 113 Samples who were members and 174 were non members.

First the model was run for data set of those who were members of Frequent Flier Program. The software used was AMOS (Analysis of Moment of Structures) which is commonly used SEM Software.

The Results of this run are as follows:

Total Number of Parameters	=	45
No. of Parameters to be estimated	=	21
Degrees of Freedom (df)	=	45 – 21 = 24
Chi square	=	42.124
df	=	24
P Value	=	0.012

Since this P value (0.012) is less than 0.05, the Null Hypothesis i.e. Model fits the data gets rejected.

Next we will have a look at Modification Indices. This will help to improve the model by introducing additional constraints. We have given below THREE Highest value Modification Indices.

Eracom4	⟷	Ers3	7.11
Eracom4	⟷	Ers2	7.54
Ert3	⟷	Eltel	4.02

First line means that Errors associated with

Eracom4 i.e. I feel Strong Sense of identification with X

And

Ers3: You like recommending X to others Co vary

It makes sense to join them as in reality also there is a relation among the responses. Similarly Eracom4 and Etr2 are also joined.

After these modifications the model was run again.

The Result is as follows:

Total Number of Parameters	=	45
No. of Parameters to be estimated	=	23 (21 + 2 New)
Degrees of Freedom (df)	=	45 – 23 = 22
Chi square	=	24.94

df = 22

P Value = 0.300

Since the P value (0.300) is higher than 0.05, the Null Hypothesis gets accepted i.e. Model fits the data.

The standardised Regression weights are given below:

Table 1: The standardised Regression weights

Standardized Regression Weights			
Variable		Variable	Estimate
Commitment	<--	Trust	0.674
BndLty	<--	Trust	0.571
BndLty	<--	Commitment	0.252
AFFCOMM1	<--	Commitment	0.866
AFFCOMM2	<--	Commitment	0.826
AFFCOMM4	<--	Commitment	0.618
TRUST2	<--	Trust	0.896
TRUST4	<--	Trust	0.75
TRUST3	<--	Trust	0.815
LONGEXP1	<--	BndLty	0.603
SAT3	<--	BndLty	0.889
RS3	<--	BndLty	0.256

By looking at the above results we can conclude the following:

Latent variable commitment has loading of 0.866, 0.826 and 0.618 on Measured Variables. AFFCOMM1, AFFCOMM2,AFFCOMM4 respectively. This shows that AFF COMM1 and AFFCOMM2 capture the concept commitment better than AFFCOMM4. (AFFCOMM4: I feel a strong sense of identification with X). Another interpretation is the Respondents deviation in Responses for this Question was high. Either one can Rephrase their question or drop it from the Analysis. The same conclusion one can draw by looking under Squared Multiple Correlations, which gives the reliability of measured variables.

AFF COMM1 : 0.75

AFFCOMM2 : 0.683

AFFCOMM4 : 0.382

Brand Loyalty is driven by THREE measured variables: RS3 and SAT3, Long Exp1.

The Standardized Regression Weights are 0.256,0.889 and 0.603 squared Multiple Correlation are 0.065,0.791 and 0.364.This shows that SAT3,(overall I am satisfied with the decision to use X) and LongExp.1: - I will continue to use services of X have higher impact on Brand Loyalty compared to RS3.(You like recommending X .to other seeking your advice). One reason for this is that standard deviation of responses of RS3 is double that of SAT3. It may be true also. Hence this variable will be retained, though mathematically it can be dropped from the model.

Goodness of Fit of the Model is as follows:

Comparative Fit Index	:	0.993
Tucker-Lewis Index	:	0.989
Named Fit Index	:	0.948
Prob. Test for close fit	:	0.62
RMS Error	:	0.35

Since all the fit indices are greater than 0.9, the model fits the data.

Table 2: Residual Variances

Squared Multiple Correlations

Variable	Estimate
Trust	0
Commitment	0.455
BndLty	0.582
RS3	0.065
SAT3	0.791
LONGEXP1	0.364
TRUST3	0.664
TRUST4	0.562
TRUST2	0.802
AFFCOMM4	0.382
AFFCOMM2	0.683
AFFCOMM1	0.75

Also RMSE < 0.05. For close test > 0.05 also confirms that model fits the data.

Residual Variances (Which is a measure of left over error) for different variables are given below:

If one looks at the Residual Error variance of Brand Loyalty given by variable Erblyt = 12% (0.12). This means model has captured the Brand Loyalty 88% which is fairly good.

Next objective is to find out whether there is significant difference in the model across segments is one representing Member of frequent flier scheme and other non-members. For this we constrain the Regression Weights from each Latent Variable to measured variable(s) to be equal to that of those obtained from the previous model.

The model is built again. The second model will have lesser number of parameter to estimate compared to first one as there are additional constraints. From statistical theory we know that the difference in the value of c^2 with respect to the difference in degrees of freedom is also c^2 distributed. Using this property one can test the Hypothesis at a given significant level whether the two models differ or not.

In our case after constraining the weights of each measured variable to Latent Variable, number of free parameter will be 17 instead of earlier number of 21.

After running the model that P value is 0.000. Since this is less than 0.05, the Null Hypothesis i.e. Model fits the data gets rejected. The details are:

Total Number of parameter	:	45
No. of parameters to be estimated	:	17
Degrees of freedom	=	45 – 17 = 28
χ^2 value	=	63.319
P	=	0.000

For a change in 4 degree of freedom, the X^2 value has increased by almost 50%.

This concludes that the Brand Loyalty is different across different Segments.

Error variance of both the models is given below:

Table 3: Error variance of the two models

Variances

Variable	Estimate Model-1	Estimate model-2	Per Cng In reg Wt
Ertrst	0.332	0.439	-32.2
Ercommt	0.21	0.388	-84.8
Erblyt	0.12	0.203	-69.2
Eracom1	0.129	0.233	-80.6
Eracom2	0.185	0.225	-21.6
Eracom4	0.47	0.577	-22.8
Etr2	0.082	0.128	-56.1
Etr4	0.25	0.253	-1.2
Ert3	0.127	0.187	-47.2
Elte1	0.501	0.348	30.5
Esat3	0.092	0.149	-62.0
Ers3	1.478	1.022	30.9

Almost all the errors have increased considerably.

Comparing the Standardized Regression Weights, the max change in weights are in measured variables: RS3 (43%), Long exp1 (23%) and the corresponding questions are:

RS3: You like recommending X to others seeking your advice.

Longexp1: I will continue to use the services of X

These are the two measured variables that affect the Brand Loyalty and the ones that discriminate the two segments.

The other information that structural equation Modeling brings out is the indirect effect on variable via an intermediately variable.

Trust influences SAT3 through Brand Loyalty (Standardized Indirect effect – 0.658)

Trust influences RS3 through Brand Loyalty (St. Indirect effect – 0.189)

Trust influences LONGEXP1 through Brand Loyalty (St. Indirect effect – 0.446)

Commitment influences SAT3 through Brand Loyalty (St. Indirect effect – 0.224)

Commitment influences RS3 through Brand Loyalty (St. Indirect effect – 0. 189)

Commitment influences LONGEXP1 through Brand Loyalty (St. Indirect effect – 0.152)

This shows that Trust exerts a greater indirect influence on Brand Loyalty than Commitment.

CONCLUSION

The above study demonstrates the power of structural equation modeling for modeling brand equity and also identifying reliable measured variables that defines concepts like Brand Loyalty, Trust ,and Commitment. If also helps one to understand the direct and indirect effect of one concept through other concepts and measured variables. Also comparison of models across Segments is also demonstrated.By controlling these variables we can improve the brand loyalty.

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