

CB-SEM and VB-SEM: Evaluating Measurement model of Business Strategy of Internet Industry in Indonesia

I Gede Nyoman Mindra Jaya¹, Nurul Hermina², Neneng Sunengsih³,
¹ Department Statistics of Padjadjaran University, Bandung, Indonesia
² Management Faculty of Widyatama University, Bandung, Indonesia
³ Department Statistics of Padjadjaran University, Bandung, Indonesia

Abstract— Structural equation modeling (SEM) is a very popular statistical analysis technique for modeling a complex system that combines factor analysis and path modeling. Factor analysis constructs the latent variables, and path analysis constructs their relationships. The latent variable or construct is measured using several dimensions, and some indicators for each dimension. There are two common approaches of SEM: Variance Based-SEM (VB-SEM) and Covariance Based (SEM). The last method is a popular choice for many disciplines because of the ability to evaluate complex model specifications using a parametric approach. However, strong assumptions are needed to produce a good result. Moreover, high variability in the data may cause the assumptions are violated such as normality and minimum sample size. VB-SEM or Partial Least Square Path Modeling (PLS-PM) becomes the best alternative when the assumptions were not satisfied. However, both methods have different objectives. CB-SEM is used for the confirmative purpose and VB-SEM for predictive purposes. This study compares the empirical performance of both SEM approaches using the same dataset to evaluate the validity and reliability of the measurement model for the Business strategy of internet industry. We found VB-SEM and CB-SEM provide similar results which indicate the questionnaire of business strategy for the internet industry is valid and reliable. However, CB-SEM is more appropriate because it was evaluated using several model fit criteria.

Keywords: Partial least square SEM; Covariance-based SEM; Maqasid syariah quality of life; Measurement model.

Index Terms— Business Strategy, CB-SEM, Reliability, VB-SEM, Validity

1 INTRODUCTION

Structural equation modeling (SEM) is the one of the most vital statistical multivariate tool for many disciplines which used to model a complex phenomenon [1]. It has ability to simultaneous evaluate the multiple regression models and accounting for measurement errors. Combine factor analysis and path modeling, SEM becomes one of the useful methods for theory testing and theory development. Factor analysis constructs the latent variables, and path analysis constructs their relationships ([2], [3]). Hair et al (2011) [1] define two family of SEM: Variance Based-SEM (VB-SEM) and Covariance Based (SEM). The last method is a popular choice for many disciplines because of the ability to evaluate complex model specifications using a parametric approach. It is commonly applied for psychology study and VB-SEM is very popular for marketing-research study. Strong assumptions are applied for CB-SEM such as normality and minimum sample size [4]. VB-SEM or Partial Least Square-SEM is a promising method that more flexible in normality and sample size assumptions.

Both SEM methods have a different objectives. CB-SEM is used for confirmative purpose and VB-SEM for predictive purpose [1]. This study compare the empirical performance of CB-SEM and VB-SEM using the same dataset to evaluate the validity and reliability of measurement model for Busniss strategy of internet industry.

2 STRUCTURAL EQUATION MODELING

SEM is an effective multivariate statistical analysis that can be used to analyse the interrelationships between latent variable simultaneously. SEM usually used to test complet theories and concepts [2]. There are two types of SEM approaches: Covariance-based technique (CB-SEM) and Partial Least Square (PLS-SEM). The most popular CB-SEM are LISREL and AMOS. While for VB-SEM is PLS-SEM. VB-SEM method is useful when CB-SEM approaches get to their limitations, specifically, in situations when the quantity of items per

latent concept becomes greatly big and parameteric assumptions are viloted [5].

2.1 Assessing Measurement Model

To evaluate the measurement model, the criterion in Table 1 is used [6].

Table 1. Assesing reflective measurement model

Criterion	Description
Composite reliability (ρ_c)	$\rho_c = (\sum \lambda_i)^2 / [(\sum \lambda_i)^2 + (\sum Var(\epsilon_i))^2]$ where λ_i is the outer loading factor to an indicator, and $Var(\epsilon_i) = 1 - \lambda_i^2$. The composite reliability must not be lower than 0.600
Indicator validity	Absolute standardized outer loading should be higher than 0.700
Average variance extracted (AVE)	$AVE = \sum \lambda_i^2 / [\sum \lambda_i^2 + (\sum Var(\epsilon_i))^2]$. AVE should be higher than 0.50
Fornell-Larker criterion	It is used for discriminant validity. The square root of AVE should be higher than correlation with all other latent variables.

2.2 Comparison VB-SEM and CB-SEM

The generall summary of VB-SEM and CB-SEM from Hair et al (2013) [7] is given in Table 2.

Table 2. VB-SEM versus CB-SEM

Criteria	VB-SEM	CB-SEM
Objective	Prediction oriented	Parameter oriented
Distribution assumption	Non-parametric	Parametric
Required sample size	Small (min. 30-100)	High (min. 100-800)
Model complexity	Large models	Large model with a lot of indicator becoms problematic
Parameter estimate	Potential bias	Stable if assumption is fulfilled
Indicator per construct	No constraint	Minimum 3 to meet identification requirements
Statistical tests for parameter estimate	Resampling	Assumption must be fulfilled
Measurement model	Reflective and Formative indicator	Reflective and Multiple input multiple causes (MIMIC)
Goodness of fit measure	None	Many

Table 3 below present the goodness of fit measure in CB-SEM [8].

Table 3. The goodness of fit measure in CB-SEM

Fit index	Description	Criteria
Chi-square	To evaluate the discrepancy between the sample and fitted covariance matrix	p.value > 0.05
Chisq/df	Chi-square is very sensitive to the sample size. Chisq/df in an alternative solution for large sampel size.	< 3
RMSEA	Chi-square are very sensitive to the number estimated parameters. The lower RMSEA is better.	< 0.08
GFI	Measure of fit between the hypothesized model and the observed covariance matrix.	> 0.90
NFI	To evaluate fit model by comparing χ^2 of the hypothesized model to the χ^2 null model	> 0.90
CFI	Compare the sample covariance matrix with the null model which assume all latent variables are uncorrelated.	> 0.90

3 MODELING USING SECOND ORDER SEM

Figure 1 displays the theoretical model of business strategy in this study to compare the two approaches of SEM method: CB-SEM and VB-SEM. We use R-software to estimate CB-SEM and VB-SEM. CB-SEM is applied using lavaan package and VB-SEM by means plspm package.

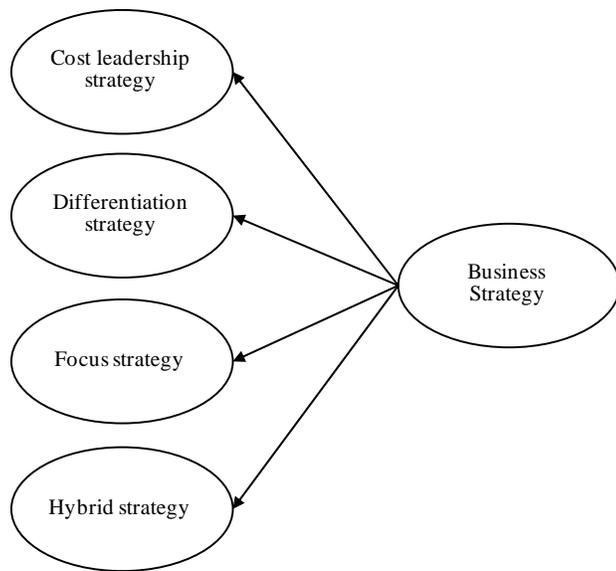


Figure 1. The theoretical model of business strategy

Table 4 provides the definition of each dimension and their respective indicators. All items were measured on a ten-point Likert-type interval scale coded as 1 = strongly disagree, to 5 = strongly agree with the given statement.

Table 4. Items Measuring the Dimensions of Business Strategy of the Internet industry

Dimension	Indicator
Cost Leadership Strategy	Control operating costs efficiently
	Set prices lower than competitors
Differentiation Strategy	Improved product quality through product bundling packages
	More responsive after sales service
Focus Strategy	Define specific customer segments as a target market effectively
	Serve the needs and desires of customers with products that fit their market segments
	Serve certain segments by providing different services
	Serve certain customer segments at lower prices
Hybrid Strategy	Implement product quality improvement
	Implement quality after sales service

4 RESULTS

4.1 Data collecting

Data was collected from 128 internet business providers in Indonesia in 2018. Cluster sampling method and web survey was used to collect the data.

Table 5. Demography of Respondent

Demography		Frequency	Percentage (%)
Education	Bachelor	70	54.7
	Master	54	42.2
	Doctor	4	3.1
Position	Manager	74	57.8
	General Manager	32	25.0
	Senior Manager	22	17.2

4.2 Model estimation

The theoretical model consisted of four reflective constructs, as illustrated in Figure 1. The result for measurement model assessment between the two SEM methods is reported in Tables 2, 3, and 4. Both CB-SEM and VB-SEM met their respective indicator loading minimum requirements as illustrated in Table 2. The minimum acceptable requirement for indicator loading in the model is 0.70 for both methods.

Table 6. Indicator Loading

Dimension	Item	VB-SEM	CB-SEM
Cost Leadership Strategy	X1	0.924	0.957
	X2	0.884	0.664
Differentiation Strategy	X3	0.927	0.861
	X4	0.924	0.828
Focus Strategy	X5	0.810	0.777
	X6	0.864	0.772
	X7	0.848	0.838
	X8	0.788	0.695
Hybrid Strategy	X9	0.929	0.851
	X10	0.928	0.852

Results in Table 6 shows that, overall the indicator loadings for CB-SEM are lower than VB-SEM as VB-SEM does not calculate factor loadings, but composite loadings. This problem is known as overestimate problem of VB-SEM. The consequence is, the composite reliability (CR) and average variance extracted (AVE) also overestimate as illustrated in Table 7. Indicator reliability was evaluated by means composite reliability

(CR). All construct achieved value higher than recommended level 0.70 both CB-SEM and VB-SEM which indicated all the indicator are acceptable. AVE is used to assess the convergent validity which is presented in Table 7. Both VB-SEM and CB-SEM results met the convergent validity when all values for each construct is greater than 0.50. AVE larger than 0.50, indicating that the construct explains more than 50% of the variance of its indicator variables.

The VB-SEM has a higher factor loading, RC, and AVE than CB-SEM which strongly indicates that VB-SEM is always bias upwards. This result is consistent with Rönkkö and Evermann (2013) [9].

Table 7. Construct Reliability and Validity

Dimension	VB-SEM		CB-SEM	
	CR	AVE	CR	AVE
Cost Leadership Strategy	0.900	0.818	0.803	0.678
Differentiation Strategy	0.923	0.857	0.833	0.713
Focus Strategy	0.897	0.686	0.855	0.596
Hybrid Strategy	0.926	0.862	0.841	0.725

For both methods, we compute discriminant validity criterion using Fornell and Larcker criterion in Table 4. Both methods satisfied discriminant validity requirements. The square root of AVE is higher than its correlations of any other dimensions.

Table 8. Discriminant Validity for CB-SEM and VB-PM (Fornell & Larcker approach)

VB-SEM					
	BS1	BS2	BS3	BS4	AVE
BS1	1.000				0.904
BS2	0.510	1.000			0.926
BS3	0.492	0.604	1.000		0.828
BS4	0.458	0.375	0.655	1.000	0.928
CB-SEM					
BS1	1.000				0.823
BS2	0.541	1.000			0.844
BS3	0.611	0.713	1.000		0.772
BS4	0.490	0.571	0.645	1.000	0.851

Moreover, the correlation construct of VB-SEM seems smaller than CB-SEM. This research supported the work of who suggested that the construct correlations

from VB-SEM are always underestimated due to the capitalization on chance correlation existing [10].

Table 9. Goodness of fit CB-SEM

Criterion	Value	Conclusion
Model Fit Test Statistic	37.997	Closed fit
Degrees of freedom	27.000	
P-value (Chi-square)	0.078	
Chisq/df	1.4073	Closed fit
Comparative Fit Index (CFI)	0.980	Closed fit
Tucker-Lewis Index (TLI)	0.966	Closed fit
Robust Comparative Fit Index (CFI)	0.977	Closed fit
Robust Tucker-Lewis Index (TLI)	0.961	Closed fit
RMSEA	0.056	Closed fit
SRMR	0.059	Closed fit

Table 9 presents the goodness of fit criterion for VB-SEM. All criterion achieved value higher than minimum level which indicates the measurement model of business strategy industry internet strongly fit with the data.

5 DISCUSSION

Debate and discussion about the application of the VB-SEM and CB-SEM methods are still ongoing. Many researchers criticize the use of VB-SEM for various reasons including: the absence of a measure of model goodness, not paying attention to measurement errors, bias, consistency and it is not based on the probability model ([11], [12]). However, VB-SEM model with good measurement error provides a good result a CB-SEM [13]. To the empirical results, both models produced similar results for business strategy measurement. The CB-SEM is more appropriate for validating and reliability measurement model. However, we cannot say that one model is generally superior to the other. The CB-SEM is more appropriate for VB-SEM to validate and confirm issues because of this model has more criteria for model evaluation and validating. VB-SEM is more suitable for predictive purpose because of the estimation procedure is focused on the increase of variance explained of the response variable. Wold (1985) [14] suggest to use VB-SEM model when the phenomenon being investigated is relatively new and the measurement models are at the explanatory phase. The use

of VB-SEM is not recommended for confirmative purposes because it does not facilitate the evaluation of model specifications.

The small sample size has always been the main reason researchers used VB-SEM compared to CB-SEM. However, although the VB-SEM model can still be estimated using a small sample size, the adequacy of the sample must still be a concern to guarantee representative results and minimize the impact of sampling error. In general, the rule-of-thumb for determining sample size is the sample size should be 5 to 10 times of the number of manifest variables in the model [10].

The other reason why researchers use VB-SEM is normality assumption. Using bootstrap procedure, VB-SEM perform well with non-normal data. On the other hand, CB-SEM is very sensitive to violations of the assumption of normality. For data do not follow the normal multivariate distribution, the goodness of fit test using Chi-square statistics perform bad commonly. If the number of sample size is relatively big, CB-SEM the robust estimator can be used to solved this problem. Hence, the CB-SEM is still a superior approach for sample size relatively big even the data do not follow multivariate normal.

Model fit becomes a serious issue for VB-SEM because of the limitation goodness of fit criterion owned. The model fit indices evaluate the extent of fitness of data to its measurement model. For the confirm model purpose, the model fits are the priority.

6 CONCLUSION

A business strategy questionnaire is important part of industrial internet research. The questioner should be valid and reliable for collecting data purposes. We found VB-SEM and CB-SEM approaches provide almost similar results. However, CB-SEM more appropriate because the model fit criteria show a better result. All the indicators with four dimension were categorized valid and reliabel. The most reliable dimension is focus strategy. It indicates the variability of the business strategy is depend on the variability of the focus strategy.

ACKNOWLEDGMENT

This paper is funded by the RFU Unpad contract: 1732 d/UN6.RKT/LT/2018. The authors thank Rector Universitas Padjadjaran. LAPAN Bandung for the temperature data and to the anonymous referee whose valuable checking has improved this paper

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