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Research article

VBSEM in E-business research: Empirical recommendations and illustrative case

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Abstract
The variance based approach to structural equation modeling (VBSEM) has been widely adopted in business research field, consumer behavior, marketing, management, tourism research. The use of VBSEM in the field of E-business is also growing. Nevertheless, questions still exist among some researchers concerning whether and how VBSEM should be used. To deal with these questions, our research offers an empirical guideline for using VBSEM and employs example from the E-business literature to make obvious how the explicit points in this guideline can be applied. The foremost contribution of this research is to present an empirical guideline for evaluating and using VBSEM that is tailored to the E-business field.
Keywords: *E-business, VBSEM, Empirical guideline*.

1. Introduction

E-business can be defined as the utilization of an electronic medium for the effecting of transactions and the sustaining of business practice as well as the development of cooperation and partnership opportunities with new clients (Matopoulos, 2007) (i.e. virtual warehouse, electronic marketplaces, and logistics brokerage systems). E-business can have enveloping influences on all facets of market rivalry since the fundamental utensil for understanding the effect of information technology on firms is the value chain – the set of actions throughout which a product/service is produced and distributed (Porter, 2001). These tricks contain pre-sale enquiry management, order payment, warehousing and storage, shipping to post-sale service, whose cost as well as value can be enhanced considerably via efficient use of information technology.

Methodical rigors as well as sophistication in investigation approaches are imperative to build theory in e-business. Nevertheless, the significance of such innovative techniques relies on researchers' enthusiasm to discover, accept and hold these approaches and think advantageously concerning the study development. Previously, the zenith e-business researches contained results that were practically without advanced data analysis. Nowadays, conversely, academic business journals in e-business field are overflowing with papers employing complicated quantitative techniques (Sarstedt, 2014). One of the mainly leading approaches in this setting is SEM (Structural Equations Modeling).

SEMs are multivariate regression models. Unlike the habitual multivariate linear regression, conversely, the response variable in one relationship in a structural equations modeling may become a predictor in another relationships; in addition, variables in a SEM can affect one another reciprocally, either or via different constructs as mediators. These equations correspond to causal relations with the variables included in the model.

Generally, there are two methods to assessing the parameters of a structural equation modeling, i.e. the covariance-based method (CBSEM) as well as the variance-based method (VBSEM). The mainstream scholars have principally adopted the first one, as epitomized by AMOS, LISREL, and EQS. CBSEM practical cases are plentifully presented (Jarvis et al., 2003) and a less prevalent method as the VBSEM has commenced to receive attention from academicians, as confirmed by the remarkable escalation of VBSEM use in several e-business research. Researchers acknowledged the beneficial proper-ties of PLS compared to CBSEM approach to estimate SEM (Wold, 1982, Jaroskog, 1982). In fact, scholars face some difficulties in their empirical works, for instance moderately less developed practical knowledge (Wacker, 1998), a deficient in consistent measurement scales (Roth, 2007), and the problem of having large samples. These problems may limit the use of CBSEM. Therefore, scholars should assess different approaches, predominantly VBSEM if structural equations modeling are employed.

Another problem related to VBSEM is that their applications are largely presented for hierarchical latent variable models with reflective relationships (Becker et al., 2012). Nonetheless, hierarchical latent variable models with reflective relationships represent are marginal (Podsakoff et al., 2006). Therefore, there is significant necessity for a detailed as well as in depth elucidation on employing and modeling hierarchical latent variable models with formative relationships in VBSEM (Becker et al., 2012).

Actually, we are not aware of any application for assessing and using VBSEM especially for the e-business investigations. Besides, it is worth noting that, like all statistical approaches, PLS necessitates a number of choices that, if not made in the approved manner, can cause improper results, analyses, and conclusions (Hair and Ringle, 2012). Consequently, based on the works of Peng and Lai (2012) and Becker et al. (2012), the purpose of the present research is to offer recommendations on how to correctly use VBSEM approach in order to publish rigorous researches in e-business field.

Against this background, this paper draws attention to VBSEM as an occasion to go forward the development as well as testing of theory in e-business field. We first pro-vide an empirical guideline of VBSEM, highlighting not just the strengths of this method but also its weaknesses. We then illustrate a real example and conclude with a discussion of further research avenues that merit greater attention.

2. Empirical guideline for estimating research using VBSEM

We present in this section the different stages that every researcher should apply in order to well perform a rigorous VBSEM analysis.

2.1 Objective of the research

Both methods estimating the parameters of a SEM have different characteristics that make them appropriate for diverse research objectives. CBSEM is principally employed to validate theories (Tenenhaus et al., 2005). This method does so by finding out how well a suggested conceptual model is proficient to estimate the covariance matrix for a practical study. On the contrary, VBSEM method is for the most part employed to build up theories in exploratory stage. Thus, according to Hair et al. (2013) VBSEM is prediction oriented. Much of the increased applications of VBSEM may be attributed to the approach’s aptitude to run problematic modeling matters that habitually occur in the social sciences (MacKenzie et al., 2011).

2.2 Sophistication of the Model

VBSEM method is useful when CBSEM approaches get to their limitations, specifically, in situations when the quantity of items per latent concept becomes greatly big. In fact, the purpose of CBSEM is to identify the matrix of model parameters (Φ) in such a manner that the consequential covariance matrix estimated by the conceptual framework ($\Sigma(\Phi)$) is as shut as possible to the empirical sample covariance matrix (S). So, the researcher should delineate a discrepancy function ($F(S, \Sigma)$), which undertakes "0" just when (S) = (Σ) and if not is positive, escalating as the variation between (S) and (Σ) augments (MacCallum et al., 1996).

Given the number of items (p) per latent variable, the scholar should attempt to determine as many of the mass possible since more observed items per latent variable cause less biased results and more established output (McDonald, 1996). In addition, in e-business investigations, scholars infrequently have more than a handful of observed indicators per latent variable in their measurement scales. In these situations, the empirical sample covariance matrix can without problems get to a size that is complicated to handle with usual computer systems since based on (p) observed indicators the empirical sample covariance matrix has ($p(p+1)/2$) different elements. Furthermore, and most likely more critically, the arithmetical power of such model would be so great that it would actuality be unfeasible to pertain any type of fittest to assess global model quality. In addition, the matter of consistency generally would not exist in VBSEM since the selection of weights would not have any effect on the path model parameters. The VBSEM global model would be so close to the conceptual model, and the difference between linear composites as well as underlying components would be-come slightly small. Thus, the scholar would be well recommended to employ VBSEM in such cases.

2.3 Data properties

A principal benefit of VBSEM over CBSEM is that it performs especially well with small sample sizes (Becker et al., 2012). Scholars must take into consideration that no statistical approach can offset the fact that smaller sample sizes go in parallel with higher sampling error, particularly when the population (N) and the sample (n) are mixed in composition. Then, the biasing influences of small sample sizes are probably to be accentuated when data are awfully skewed. Notwithstanding VBSEM is considered to be vigorous when employed on highly non-normal data (Becker et al., 2012), such data meagerness blow up bootstrapping standard errors, thus minimizing the statistical power of the approach. Making an allowance for the propensity of VBSEM to underestimate the structural model (Vinzi et al., 2010) skewed data may represent an apprehension in amalgamation with small sample sizes.

An additional advantage of VBSEM is its aptitude to process diverse ratio scaled constructs (ordinal, nominal, and interval) (Diamantopoulos and Siguaw, 2006). The utilization of categorical constructs in VBSEM must be used with concern as the number of binary items and the place of the corresponding variable in the structural model may perhaps confine the utilization of categorical constructs. For example, a concern crops up if a binary single construct is employed to assess an endogenous latent variable representing a purchase situation. In the last structural estimation of the VBSEM algorithm, the endogenous latent variable is regressed on the forerunner variables. As the construct becomes its measure, nevertheless, and so has just two values (purchase versus do not purchase), a fundamental principle of the regular least squares regression is defiled. Scholars should be up to date, hence, with the basic steps in the VBSEM algorithm (Hair et al., 2014) to steer clear of framework system that are problematic in this respect.

2.4 Specifying reflective / formative constructs

The reflective mode presupposes that the observed variables are functions of the primary latent variables in the actual blocks. Alternatively, the formative mode outlines the latent variables as linear functions of the observed variables. A principal contributing to the misspecification of measurement models in e-business modeling is the oversight of clearly specifying the higher-order factor of the important variable (Ibrahim, 2014). It is well known that a main condition for conceptualizing as well as operationalizing multidimensional concepts is that they should be anchored in theory which should specify the number of components and their affiliation to the higher-order factor (Ibrahim and Najar, 2007). Numerous underlying principles have been advanced to advocate the utilization of these hierarchical latent construct frameworks over the use of frameworks containing only lower-order dimensions. Partisans of the use of higher-order constructs assume that they tolerate for more hypothetical thriftiness and decrease model sophistication. Using CBSEM to conceptual frameworks with formative constructs frequently leads to unidentified models (Wilson and Henseler, 2007). This is for the reason that applying formative items in CBSEM means null covariance between items, and the model can barely be resolved once it comprises a considerable number of extra parameters (Chin, 1995). Since the algorithms carried out in a VBSEM analysis usually comprise a chain of regular least squares analyses (Marcoulides and Saunders, 2006), identification is not a concern for recursive models. This property offers VBSEM a benefit in assessing conceptual frameworks with formative indicators. VBSEM can evaluate conceptual models with both reflective and formative indicators devoid of escalating model sophistication (Diamantopoulos and Siguaw, 2006). Becker et al. (2012) elucidate a typology of hierarchical latent variable models and offer an general idea of diverse methods that can be employed to assess the parameters in these models: (i) the repeated indicator method, (ii) the two-stage method, and (iiii) the hybrid method.

i. The reflective-reflective model

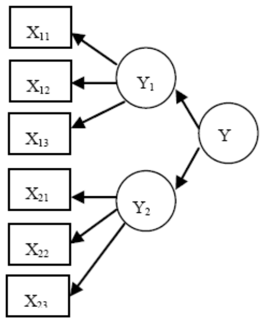

Fig. 1. The reflective-reflective model

This category of hierarchical latent construct model is mainly suitable if the purpose of the research is to determine the common component of different associated concepts. Reflective indicators should contain a number of dimensions conceptually identical which conflicts with the vision of compound principal components. Consequently, it is either needless to model the lower-order indicators as different constructs since they should be indistinguishable consistent with a reflective sense or, if manifold different components undeniably exist, these components should be modeled as formative, producing a reflective-formative latent variable model (Becker et al., 2012).

ii. The reflective-formative model

The lower-order variables are reflectively assessed indicators that do not split an abstract concept however outline a common concept that completely mediates the effect on following endogenous constructs (Wold, 1982).

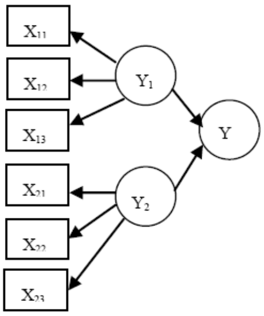

Fig. 2. The reflective-formative model

Every so often, these forms of hierarchical latent variables are furthermore applied to report the measurement error of the items of a formative variable: the items are operationalized as reflective to clearly model their measurement error (Chin, 1995).

iii. The formative-reflective model

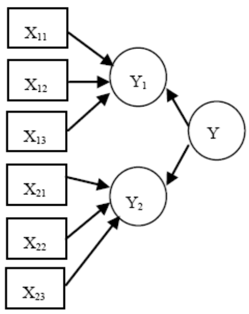

Fig. 3. The formative-reflective model

The higher-order variable is a common concept of numerous particular formative lower-order variables. For example the purpose of such a higher-order relationship quality (i.e.; e-trust, e-loyalty, e-commitment) construct would be to stand for the common part of a number of items that assert to operationalize the identical thing yet employing diverse approaches to achieve this task. This technique helps to conquer the limitations of each single item (Becker et al., 2012).

iv. The formative-formative model

The lower-order variables are formatively operationalized variables which outline a more general variable. This is frequently done if a number of e-business significant concepts are included under the abstract concept.

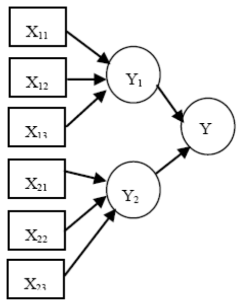

Fig. 4. The formative-formative model

Nonetheless, counter to the formative-reflective form model, a formative-formative form model would not encompass diverse items other than dissimilar features of the variable. Furthermore, the forma-tive-formative form model can also be practical to makeup a compound formative variable that various items into numerous sub-constructs (Becker et al., 2012).

2.5 Estimation of hierarchical latent variable models in VBSEM

For the reason that, VBSEM involves the calculation of global construct for every latent variable in the model. Researchers propose three techniques modeling hierarchical latent variables. First, the repeated indicator technique (Wold, 1982). Second, the sequential latent variable score technique or two-stage technique (Ringle et al., 2012), and third the hybrid technique (Wetzels et al., 2009).

2.5.1 The repeated indicator technique

A higher-order latent variable can be formed by identifying a latent variable which corresponds to all the observed variables of the original lower-order latent variables (Diamantopoulos and Siguaw, 2006). Thus, the observed variables are employed two times: First, for the first-order latent variable and second for the second-order latent variable.

2.5.2 The sequential latent variable score technique, or two-stage technique

It assesses the construct scores of the first-order constructs in a first-stage model devoid of the second-order construct present, and then employs these first-stage construct scores as items for the higher order latent variable in a detach second-stage estimation (Wetzels et al., 2009).

2.5.3 The hybrid technique

It performs as the repeated indicator technique nevertheless employs each observed constructs no more than one time in a model to keep away from synthetically interrelated residuals. It divides the indicators of each first-order construct and employs one half to assess the first-order construct and the other half to assess the second-order construct, consequently keeping away from the recurring use of manifest indicators in the model (Wilson and Henseler, 2007).

2.5.4 Structural model assessment

VBSEM employs a bootstrapping method to assess standard errors and the importance of parameter estimates (Hair et al., 2013). Unlike CBSEM, VBSEM does not have a typical goodness-of-fit statistic, and efforts to found a analogous statistic have demonstrated highly awkward (Ringle et al., 2003). As an alternative, the evaluation of the model's quality is rooted in its capability to predict the endogenous variables. The following indexes make possible this estimation; (i) the coefficient of determination (R^2), (ii) the cross-validated redundancy (Q^2) and (iii) the path coefficients. Before this appraisal, the scholar should examine the inner model for possible collinearity between the predictor variables. They also should determine that the regression outputs are not biased by collinearity concerns. This stage is similar to the formative measurement model estimation, with the dissimilarity being that the scores of the exogenous latent variables are employed as input for the VIF evaluations. The next stage involves assessing the (R^2) value of all endogenous variables.

2.7 Evaluation of VBSEM output

Assessing VBSEM outputs means effecting two steps. The first step looks at the measurement models, with the examination changing depending upon whether the model contains reflective constructs, formative constructs or both. If the measurement model estimation shows satisfactory findings, the scholar go to the next step, which involves estimating the inner model (Ringle et al., 2003) and examining if the path relations are significant and testing the proposed hypotheses. For the formative models, scholars must account indicator weights, which correspond to each formative indicator's loading to the formative index. They should calculate not only the statistical significance, but in addition the confidence interval of structural paths (Sharma and Kim, 2013). According to Sarstedt et al. (2014), if the hypothesis is accepted, the rigor of the technique can be judged by means of the width of the confidence interval. Scholars can employ bias-corrected confidence intervals as a suitable method for checking the significance of the path coefficients assessed by VBSEM (Wetzels et al., 2007).

3. An illustrative case of using VBSEM

In this section, we illustrate an example of employing VBSEM to estimate a conceptual model that incorporates both reflective as well as formative variables.

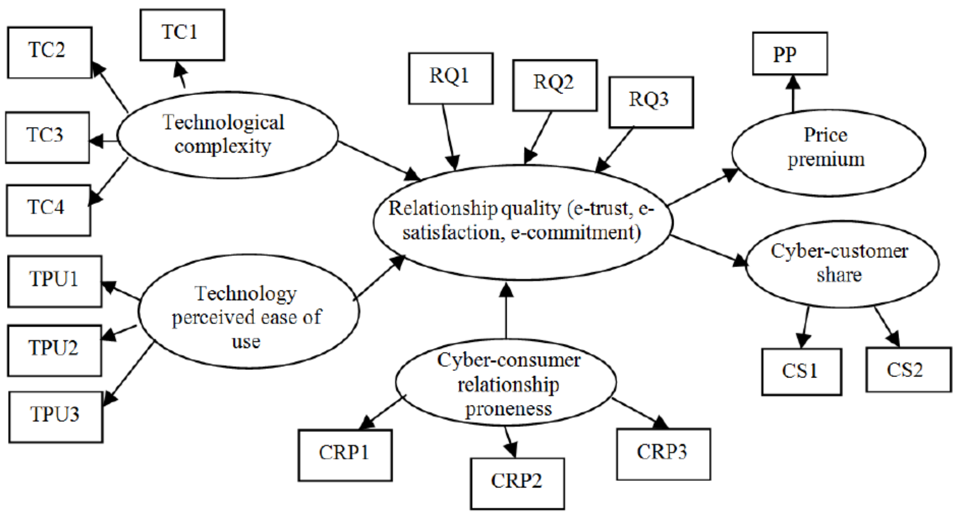

Fig.5. The conceptual model tested in E-business setting

The conceptual model is showed in Fig. 5, in which relationship quality is considered as a formative variable, and cyber-consumer relationship proneness, technological complexity and technology perceived ease of use are the antecedents, and price premium as well as cyber-customer share are the outcomes. We utilize data from a practical research to test the conceptual research model. The sample size is 239 online shoppers. The measurement scales are exposed in Tables 1 and 2.

We employ SmartPLS 2.0 in order to assess the suggested conceptual model. For the reason that the criteria for estimating reflective and formative variables are dissimilar, we chose to estimate the two types of variables independently. The item loadings, composite reliability (CR), and average variance extracted (AVE) of the reflective variables are shown in Table 1. All item loadings are larger than 0.70 and significant at the 1% level, demonstrating convergent validity at the observed indicator level. All average variance extracted values are beyond 0.50, signifying convergent validity at the construct level. All composite reliability values are larger than 0.70, showing satisfactory reliability.

Table 1: Measurement properties of reflective constructs

Constructs	Indicators	Item Loading	T-Stat	Composite reliability	Communality (AVE)
Technological Complexity	I have no difficulty in reading the information displayed on the mobile computing device's screen (TC1)	0.8976	45.5142	0.8932 92781805	0.7412
	I have no difficulty in accessing the e-store (TC2)	0.7821	37.2154		
	I have no difficulty in reading the information displayed on e-store website (TC3)	0.8246	12.3254		
	Generally, using the web site is an easy task for me (TC4)	0.7299	76.3849		
Technology Perceived Ease of Use	Shopping online would be easy (TPU1)	0.8881	67.9735	0.8862	0.7021
	Reading information about products of E-store is simplistic (TPU2)	0.8897	32.3279		
	E-store is ergonomic, uncomplicated and Friendly (TPU3)	0.8749	14.7542		
Cyber-consumer relationship proneness	Generally I am someone who likes to be a regular cyber-customer of an e-store (CRP1)	0.7821	60.0314	0.9001	0.8234
	Generally I am someone who wants to be a steady cyber-customer of the same e-store (CRP2)	0.7795	39.7530		
	Generally I am someone who is willing to go the extra mile to visit the same store (CRP3)	0.7899	41.8621		
Cyber-consumer share	Of the potential products or services you could purchase from this e-store, what percent share does this store currently have? (CS1)	0.9107	12.1354	0.7996	0.6987
	Of the potential products or services you could purchase from this e-store, what percent share do you estimate this firm will have 3 years from now? (CS2)	0.9322	51.4712		
Price premium	What price premium (average) would you pay to deal with this e-store versus another store with similar products/services? (PP)	1	-		

Table 2: Measurement properties of formative constructs

Construct	Indicators	Item weight	T-Stat	VIF
Relationship quality	e-Satisfaction (RQ1)	0.2846	5.4148	1.089
	e-Trust (RQ2)	0.4215	3.3159	1.102
	e-Commitment (RQ3)	0.3421	2.2251	1.438

Table 3: Structural estimates

Path	VBSEM result		OLS regression result		
	Coefficient	T-Stat.	Coefficient	T-Stat.	Power
Technological Complexity --> Relationship quality	0.3120	9.0325	0.317	3.745	0.9875
Technology Perceived Ease of Use --> Relationship quality	0.2689	7.3810	0.281	9.175	0.9524
Cyber-consumer relationship proneness --> Relationship quality	0.2354	8.254	0.321	2.499	0.9636
Relationship quality --> Price premium	0.3489	6.8541	0.198	3.478	0.9258
Relationship quality --> Cyber-customer share	0.2891	4.2189	0.241	4.880	0.9989

Concerning the formative variable, we look at the formative indicator weights, multicolinearity among items, face validity, discriminant validity, content validity, and nomological validity of the formative variable. For each formative indicator, we look at its weight, scale, and sign. Each indicator weight is larger than 0.10 (Adreev et al., 2009) and the sign of the indicator weight is in agreement with the basic theory. All VIF indexes are under 3 (Ibrahim and Najjar, 2007), demonstrating that multi-collinearity is not severe. To check the discriminant validity of the formative variable relationship quality, we calculate the average of sub-indicator item correlations for this variable and the average of sub-indicator correlations among this variable and other variables. We notice that the average of sub-indicator correlations is larger than the average of sub-indicator correlations.

We evaluate the nomological validity of the relationship quality variable by investigating the structural paths of its inputs along with outputs. Our findings show significant and positive associations connecting relationship quality and its 3 antecedents and 2 outputs, supporting the nomological validity of relationship quality measures.

The outputs of the inner model estimation are exposed in Tables 3. We estimate the inner model by means of the bootstrap method with 200, 500 and 1000 times of re-sampling and the scale and significance of the structural paths are reliable. Concerning the global quality of the conceptual model, we calculated the GF index (Goodness of Fit = 0.3129). Our sample size of 239 is well more than the minimum sample size condition as determined by the "10 times" rule of thumb. The most sophisticated part in our model is the reflective construct technological complexity, which has 4 reflective indicators. As a final point, we test the vigor of the VBSEM findings. Since our conceptual model incorporates both reflective and formative variables, we are unable to perform CBSEM and compare VBSEM findings with CBSEM findings. Instead, we compute the average of the indicators within each variable and subject these aver-age values to the ordinary least squares regression (OLS). The OLS regression findings are mostly in agreement with the VBSEM findings (Table 3).

4. Discussion and conclusion

Structural equations modeling is one of the most well-known advanced methods utilized in e-business research. It is beyond a shadow of a doubt to find a topic of a most important business journal in which structural equations modeling is not employed in at least one of the research papers. As a number of scholars illustrate, main advances have been made in e-business in the last decades, and the future of this discipline of e-business research looks bright. Nevertheless, it comes into sight that e-business modelers have not taken advantage of the benefits offered by VBSEM method.

We consider that e-business modeling is at the core of the concept of e-business science. Science is a process and in this process, theory testing is compulsory to build up valid e-business models. Then, the e-business model is carried out empirically, founded on theory based insights, managerial rulings and so forth. E-business modelers learn from this to purify and check again their conceptualizations, which are afterward used in concrete e-business contexts, et cetera. We consider that the triangulation stuck between theory testing and experimental findings derived from decision making will play a significant task in harmonizing the both contradictory demands of model minimalism and comprehensiveness.

As theories in e-business research turn out to be more nuanced (Brahm, 2011), it becomes indispensable to have approaches up to managing more multifaceted model arrangements. VBSEM demonstrates chiefly advantageous in this respect, as it permits assessing models with numerous variables, structural model relationships as well as several indicators per variable, situations which usually obstruct the use of conventional methods to structural equations modeling. Moreover, VBSEM is up to handling data inadequacies for instance skewed data and puts up formatively measured variables, the final of which have newly put on escalating importance in a range of fields (Williams et al, 2009, Weitzels et al., 2009, Wang and Wang, 2012, Shook et al., 2004, Sharma et Kim, 2013, Sarstedt et al, 2014, Ringle et al., 2012).

The present research endeavors to present an empirical as well as realistic instruction that assists e-business scholars to estimate and utilize VBSEM. The use of VBSEM has been budding in the business and management research and will likely gain more reputation. Given the specific defies practical scholars face, such as the complicatedness of obtaining outsized samples and a necessity of well-established measurement scales (Peng and Lai, 2012), VBSEM can be potentially useful methods to structural equations modeling. Since several scholars are unfamiliar with VBSEM, a specific instruction that focuses on practical applications rather than the technical details of VBSEM will be chiefly helpful. The most important contribution of our research is to offer an empirical guideline for using VBSEM with clarifying examples from the e-business discipline. This guideline is expected to help perk up the methodology rigor of VBSEM use in e-business research.

Even though VBSEM has been employed in a diversity of research contexts, the scope to which it has been employed is far less than that of CBSEM in most disciplines. The somewhat restricted utilization of VBSEM compared with CBSEM in many discipline research fields denotes scholars' general prudence about the weak spots of the VBSEM approach (Peng and Lai, 2012). In fact, econometrically, CBSEM is better than VBSEM in the sense that parameter estimates are unbiased (Chin, 1995). Consequently, if CBSEM hypotheses are found, scholars must robustly decide using CBSEM. Nevertheless, we recommend that problems related to VBSEM should not prevent it as an alternative potential analysis method since no practical approach is faultless. If the conditions of the VBSEM technique are found as well as it is applied correctly, it can be an important data analysis tool.

Our call to give VBSEM its due in e-business modeling should not be considered as a proposal that VBSEM is for all time preferable to other methods. VBSEM is surely not the solution to all modeling challenges. VBSEM is stronger in theory testing than decision making. Our standpoint is that e-business academicians must use VBSEM in the situations where CBSEM is unfeasible because of the absence of a number of fundamental CBSEM conditions (e.g., for example little sized sample and skewed sample) or model identification cases. It is noteworthy that VBSEM is not a rival approach to CBSEM. Based on the purpose of the study, the data properties, the complexity of the model, and the degree of abstract and empirical advance, the VBSEM method may be more suitable in some situations. In actual fact, according to several researchers, CBSEM and VBSEM are complementary rather than rival approaches, and both have an accurate underlying principle of their own (Peng and Lai, 2012).

Even though we argue that academicians should not prevent the alternative of employing VBSEM, we go up against accommodating VBSEM as the favored method to structural equations modeling without a cautious appraisal of its applicability (Peng and Lai, 2012). Scholars must be vigilant in estimating their model hypotheses and data prerequisites, particularly the sample size condition since it is frequently mentioned as the major rationale for using VBSEM. For the reason that VBSEM is not a "silver bullet" (Marcoulides and Saunders, 2006) to be used with samples of whichever size, scholars must reflect on a range of factors and act upon rigorous investigation to decide whether the sample size is sufficient to hold up the statistical assumption. As scholars begin to recognize the prospective of VBSEM, we anticipate that more scholars will acutely consider VBSEM as a potential structural equations modeling approach. We hope our research can be used as a valuable guideline to assist practical explorations assess e-business research using VBSEM.

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