PLS-SEM or CB-SEM: updated guidelines on which method to use

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Abstract: Numerous statistical methods are available for social researchers. Therefore, knowing the appropriate technique can be a challenge. For example, when considering structural equation modelling (SEM), selecting between covariance-based (CB-SEM) and variance-based partial least squares (PLS-SEM) can be challenging. This paper applies the same theoretical measurement and structural models and dataset to conduct a direct comparison. The findings reveal that when using CB-SEM, many indicators are removed to achieve acceptable goodness-of-fit, when compared to PLS-SEM. Also, composite reliability and convergent validity were typically higher using PLS-SEM, but other metrics such as discriminant validity and beta coefficients are comparable. Finally, when comparing variance explained in the dependent variable indicators, PLS-SEM was substantially better than CB-SEM. Updated guidelines assist researchers in determining whether CB-SEM or PLS-SEM is the most appropriate method to use.

Keywords: structural equation modelling; SEM; PLS-SEM; CB-SEM.

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1 Introduction

Applications of structural equation modelling (SEM) have increased substantially in recent years (Matthews et al., 2016b; Rutherford et al., 2011, 2012). This is primarily due to the method's improved ability to assess the reliability and validity of multi-item construct measures as well as test structural model relationships (Bollen, 1989; Hair et al., 2012b). SEM is a combination of two powerful statistical approaches: exploratory factor analysis and structural path analysis, which enables simultaneous assessment of the measurement model and the structural model (Lee et al., 2011). Moreover, the variance explained in the dependent variable(s) is larger using SEM than multiple regressions because it accounts for both direct and indirect effects (Lee et al., 2011).

Two SEM methods are available for researchers to choose from: covariance-based SEM (CB-SEM; Jöreskog, 1978, 1993) and variance-based partial least squares (PLS-SEM; Lohmöller, 1989; Wold, 1982). Understanding the differences between the two methods is an important factor when deciding which of the two approaches should be used in your research. CB-SEM is primarily used for confirmation of established theory (i.e., explanation). In contrast, PLS is a prediction-oriented approach to SEM, primarily used for exploratory research, but also appropriate for confirmatory research (Sarstedt et al., 2014a). Specifically PLS-SEM overcomes the seeming dichotomy between confirmatory and predictive research, since researchers using the method expect their model to have high predictive accuracy, while also being grounded in well-developed causal explanations (Sarstedt et al., 2018). Gregor (2006, p.626) refers to this interplay as explanation and prediction theory, noting that this approach "implies both understanding of underlying causes and prediction, as well as description of theoretical constructs and the relationships among them". This perspective aligns well with most types of business research, which typically aims at testing a theory (i.e., explanation) while offering recommendations for management practice (i.e., prediction).

The purpose of this paper is to present a direct comparison of the two SEM methods, and discuss the differences. To do so, we first describe the two approaches and their underlying differences. We then apply both methods to the same theoretical model and data to empirically compare how the solutions differ, and to demonstrate their strengths and weaknesses. This will facilitate understanding how the results differ, and thereby provide further guidance on selecting the best method.

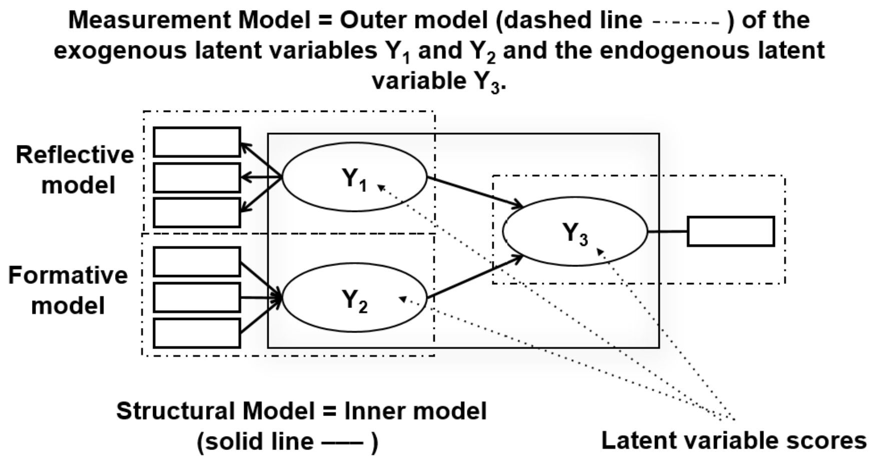
2 Comparing CB-SEM and PLS-SEM

The statistical objectives of the two SEM methods differ substantially. The statistical objective of CB-SEM is to estimate model parameters that minimise the differences between the observed sample covariance matrix (calculated before the analysis) and the covariance matrix estimated after the revised theoretical model is confirmed (Hair et al., 2012b). In contrast, the statistical objective of PLS-SEM is to maximise the variance explained in the dependent variable(s) (Hair et al., 2012a).

A fundamental difference between the two methods is that CB-SEM is based on the common factor model, whereas PLS-SEM is based on the composite model (Hair et al., 2017c). The common factor model assumes the analysis should be based only on the common variance in the data, so the attempt to develop a solution starts by calculating the covariance between the variables in the study, and only that common variance is used in the analysis. Thus, the specific variance and the error variance are removed from the analysis before the theoretical model is examined. One limitation of this approach is the removal of specific variance that could justifiably be used to predict the dependent variables in the theoretical model. Note that some measurement theory scholars reject the inclusion of specific variance while others support it. In contrast, the composite model includes common, specific, and error variance, and thus uses all variance from the independent variables that can help to predict the variance in the dependent variable(s). A limitation of this approach is that it includes some error variance if that variance helps to predict the dependent variable(s). The composite model approach, therefore, can more effectively maximise the variance explained in the dependent variable(s).

Because of random error included in composite models and indeterminacy in common factor models [i.e., an infinite number of different sets of construct scores that will fit the model equally well; Grice (2001) and Steiger (1979)] both approaches produce only approximations of the conceptual variables the constructs seek to represent (Rigdon et al., 2017). Or as Rigdon (2016, p.602) notes, "common factor proxies cannot be assumed to carry greater significance than composite proxies in regard to the existence or nature of conceptual variables".

Figure 1 Theoretical SEM and constructs



The statistical model underlying SEM consists of two elements, as illustrated in Figure 1. The inner model (also referred to as structural model) represents the structural paths between the constructs, and the outer models (also referred to as measurement models) represent the relationships between each latent variable construct and the associated indicator variables. In addition, there are two types of variables – those that explain other constructs in the model, called exogenous latent variables, and those that are being explained, called endogenous latent variables (Hair et al., 2017c). The outer measurement model is structured differently depending on the type of measurement. If the constructs are measured with formative indicators they are represented by arrows pointing from the indicator to the latent construct (Sarstedt et al., 2016). In contrast, reflective 'effects' variables (Sarstedt et al., 2016) are represented by arrows pointing from the construct to the indicator (Hair et al., 2017c). These different relationships for the two measurement models influence the calculation of solutions and if incorrectly specified introduce bias in the results. In Figure 1, the Y_1 construct is measured reflectively while the Y_2 construct is measured formatively. The Y_3 construct is a single item measure.

When using SEM qualitative measures such as face validity are not considered sufficient evidence of validity. Instead, researchers should draw on quantitative measures that allow for more precise assessments. To assess reflective measurement models, internal consistency reliability as well as convergent and discriminant validity must be established. Internal consistency reliability was traditionally assessed using Cronbach's alpha. Composite reliability is recommended as more appropriate, however, since it considers the indicators' differential weights (Chin, 1998; Dijkstra and Henseler, 2015), whereas Cronbach's alpha weights the indicators equally (tau equivalence).

Convergent validity is evaluated by examining the outer loadings of the indicators to determine the average variance extracted (AVE) from each construct. The outer loadings should exceed 0.708 because the square of that number indicates the construct score includes at least 50% of the variable's variance (Henseler et al., 2015). AVE is a summary indicator of convergence calculated from the variance extracted for all items loading on a single construct (Hair et al., 2010). The rule of thumb for adequate convergence is an AVE > 0.50, indicating that more than half of the indicator variance is included in the construct score (Hair et al., 2017c).

Assessment of convergent validity for formative measurement models is quite different since internal consistency reliability is not appropriate. Determining convergent validity for formatively measured constructs requires including additional reflectively measured variable(s) in the nomological net of each formative construct in the survey so that convergent validity can be calculated. In addition to convergent validity, formatively measured constructs are assessed based on the statistical significance and size of the indicator weights as well as collinearity among indicators (Hair et al., 2017c).

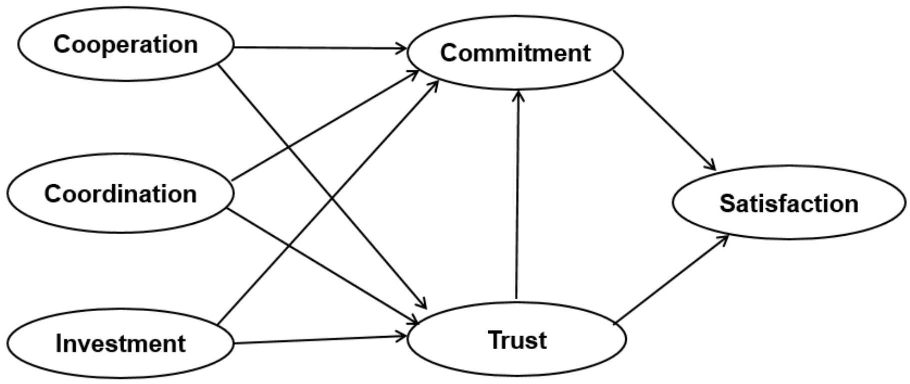
Discriminant validity denotes that a construct is empirically unique from the other constructs in the SEM (Hair et al., 2010). That is, establishing discriminant validity means that each construct captures a unique phenomenon not represented by any other construct in the model (Hair et al., 2017c). A common approach to assess discriminant validity is the Fornell-Larcker criterion (1981), which compares the AVE (shared variance within) of the constructs to the squared correlation between the constructs (shared variance between). For variance-based SEM (PLS-SEM), a more precise measure of discriminant validity, heterotrait-monotrait ratio of correlations (HTMT), was recently proposed (Henseler et al., 2015). In contrast, the Fornell-Larcker criterion continues to be the most widely applied discriminant validity approach with CB-SEM, although Voorhees et al. (2016) recommend HTMT.

CB-SEM is a parametric statistical method so statistical significance is a standard output of that technique. PLS-SEM, however, is a non-parametric method, which hinders the immediate determination of inference statistics. Instead, researchers rely on bootstrapping (typically using 5,000 samples) to derive standard error estimates of model parameters, which facilitate significance testing. For both SEM methods, structural relationships are evaluated by the size and significance of the beta coefficients. Structural model evaluation in PLS-SEM also considers the model's predictive capabilities, typically using the coefficient of determination (R^2 value), which measures the model's in-sample predictive power (Hair et al., 2017c, 2017d). In contrast, for CB-SEM, goodness of fit (GOF) is the appropriate measure to evaluate the measurement and structural models. GOF is measured by the Chi-square statistic, which indicates the difference between the sample covariance matrix and the estimated covariance matrix. Other means of assessing GOF when using CB-SEM are the various heuristics such as CFI, GFI and RMSEA. There is no established GOF measure for PLS-SEM.

3 Application of the two methods

Figure 2 displays the theoretical model that will be examined, which is based on the trust-commitment theory developed by Morgan and Hunt (1994). There are three exogenous (independent) variables: investment, coordination, and cooperation. There are three endogenous variables: commitment, trust, and satisfaction.

Figure 2 Conceptual model of structural relationships



The data used to obtain the solutions for the examples in this article is from the Payan et al. (2016) study. The items involve aspects of the business relationship between the firm and a supplier (respondents indicated a major supplier they interacted with in the last year), and are shown in Table 1. All items were measured on a five-point Likert-type scale (1 = strongly disagree, 5 = strongly agree). Cooperation is measured using five items that seek to understand whether the relationship between the firm and supplier is cooperative. Coordination is captured via six items that look at the coordination of planning and activities between the firm and it is supplier. Relationship investment is measured with five items that identify the level of time, resources and marketing investment made by the firm as it relates to their supplier. Trust assesses the level of fairness and trustworthiness between the firm and the supplier based on five items. Commitment is measured with six items and indicates the intention to continue working with the supplier. Finally, relationship satisfaction with supplier is measured with six items reflecting the relationship with the identified supplier. Note that this comparison of results is not meant to represent all CB-SEM and PLS-SEM model comparisons, but rather to be a typical representation of what researchers are likely to encounter.

Table 1 Questionnaire items and construct definitions

Investments (Inv): the extent to which a firm has invested time and resources into developing the specific relationship. Items were adapted from the specific investment scales by Heide and John (1992).

a My firm has made significant investments in resources that are useful only to this supplier.

b We have customised a consequential portion of our business in dealing with this supplier.

c We have tailored major parts of our business to accommodate the needs of this supplier.

d We have aligned a major part of our marketing activities with those of this supplier.

e My firm invests a significant amount of time acquiring knowledge about the unique aspects of the products we carry for this supplier.

Cooperation (Coop): a spirit of willingness of one firm to work with another firm. Items were borrowed and modified from the cooperation scale developed by Skinner et al. (1992).

a Our relationship with this supplier is cooperative.

b There is a cooperative attitude between my firm and this supplier.

c My firm prefers to cooperate with this supplier

d My firm prefers to get along with this supplier.

e My firm's cooperation with this supplier is a priority.

Coordination (Cord): joint activities that take place between firms. Items were adapted from the coordination scale of Guiltinan et al. (1980) and the joint action scale of Heide and John (1992).

a We work jointly with this supplier.

b Our implementation plans are formed jointly with this supplier.

c We work jointly with this supplier on issues that affect both firms.

d Our processes and/or procedures are coordinated with those of this supplier.

e Our activities are coordinated with the activities of this supplier.

f We attempt to conduct business in unison with this supplier.

Commitment (Comt): an enduring desire to maintain a relationship. Items were adapted from the commitment scales of Morgan and Hunt (1994) and Anderson and Weitz (1992).

a We are committed to doing business with this supplier.

b We'd like to continue our work with this supplier.

c We have a high level of commitment to this supplier.

d We intend to do business with this supplier well into the future.

e We are dedicated to continuing to do business with this supplier.

f We are resolute about future intent to do business with this supplier.

Satisfaction (Sat): the positive affective state resulting from the appraisal of all aspects of a firm's working relationship with another firm. Items were adapted from the satisfaction scales by Andaleeb (1996).

a Our firm is comfortable about its relationship with this supplier.

b The relationship between the two firms is positive.

c Our relationship with this supplier reflects a happy situation.

d Our firm is content about its relationship with this supplier.

e The relationship between our firms is trouble-free.

f The relationship between the two firms is satisfying.

Table 1 Questionnaire items and construct definitions (continued)

Trust (Tru): the expectation that another business can be relied on to fulfills obligations. Items were adapted from the interorganisational trust scale of Zaheer et al. (1998).	
a	This supplier has always been fair in its negotiations with us.
b	This supplier does not use opportunities that arise to profit at my firm's expense.
c	We can rely on this supplier to keep promises made to us.
d	We are not hesitant to do business with this supplier when the situation is vague.
e	This supplier is trustworthy.

4 Model results: direct comparison of PLS-SEM and CB-SEM

The theoretical model consists of six constructs, all measured reflectively. Measurement model assessment is reported in Tables 2 and 3. Indicator (item) reliability is assessed based on the outer loadings for each latent variable. Guidelines for both types of SEM indicate an outer loading of greater than 0.708 is recommended to retain an item (Lohmöller, 1989). Results of the PLS-SEM estimation using SmartPLS 3 (Ringle et al., 2015) indicate loadings of all 33 items for the exogenous (see Table 2) and endogenous (see Table 3) constructs are greater than 0.708. In contrast, 11 of the 33 items were removed (---) when using the CB-SEM method in order to achieve acceptable GOF. Retention of all the indicators using PLS-SEM improves the reliability and validity of the measurement and structural model results. In addition, the loadings for PLS-SEM are generally higher than those of CB-SEM, further improving the construct validity with PLS-SEM.

Internal consistency reliability is assessed using composite reliability. For both PLS-SEM and CB-SEM, all constructs exceed the recommended 0.70 level (Hair et al., 2017c). Convergent validity is measured using AVE. Again, for both PLS-SEM and CB-SEM, the values for all constructs are greater than the 0.50 guideline (Table 4), indicating that the construct explains more than half of the variance of its indicators (Hair et al., 2017c). But the PLS-SEM results are higher than using CB-SEM on almost all values for both the composite reliability and the AVEs.

Discriminant validity assessment by means of the Fornell-Larcker criterion produces divergent results for PLS-SEM compared to CB-SEM. Whereas the Fornell-Larcker criterion is also met with PLS-SEM, for CB-SEM, the results indicate for one comparison (trust and satisfaction) the constructs are not unique. As a result of this violation of discriminant validity guidelines, the CB-SEM model would have to be modified further in an effort to achieve discriminant validity, most likely by deleting one or more additional indicators. Thus, the discriminant validity results for PLS-SEM are acceptable using both methods, whereas there is a problem with the CB-SEM results. In contrast, with values below 0.90, the HTMT criterion indicates that discriminant validity has been met (Henseler et al., 2015). This results holds for both PLS-SEM and CB-SEM as the HTMT criterion solely rests on indicator correlations, whose values are independent of the SEM method used.

Table 2 Indicator reliability – outer loadings for exogenous variables

	PLS-SEM			*CB-SEM*		
	Commitment	*Cooperation*	*Coordination*	*Commitment*	*Cooperation*	*Coordination*
Inv_a	0.791			0.775		
Inv_b	0.852			0.847		
Inv_c	0.899			0.921		
Inv_d	0.858			0.749		
Inv_e	0.805			---		
Coop_a		0.840			---	
Coop_b		0.879			---	
Coop_c		0.873			0.858	
Coop_d		0.840			0.870	
Coop_e		0.799			0.758	
Cord_a			0.832			---
Cord_b			0.892			---
Cord_c			0.860			0.782
Cord_d			0.849			0.896
Cord_e			0.831			0.817
Cord_f			0.810			---

Note: (---) Represents deleted indicators.

Table 3 Indicator reliability – outer loadings for endogenous variables

	PLS-SEM			*CB-SEM*		
	Investment	*Satisfaction*	*Trust*	*Investment*	*Satisfaction*	*Trust*
Comt_a	0.709			---		
Comt_b	0.790			---		
Comt_c	0.812			---		
Comt_d	0.831			0.855		
Comt_e	0.871			0.853		
Comt_f	0.823			0.874		
Sat_a		0.884			---	
Sat_b		0.899			0.874	
Sat_c		0.911			0.915	
Sat_d		0.916			0.902	
Sat_e		0.766			---	
Sat_f		0.878			0.840	
Tru_a			0.900			0.872
Tru_b			0.789			0.722
Tru_c			0.850			0.816
Tru_d			0.773			0.703
Tru_e			0.915			0.910

Note: (---) Represents deleted indicators.

Table 4 Construct reliability and validity

	PLS-SEM		CB-SEM	
	Composite reliability	*Average variance extracted (AVE)*	*Composite reliability*	*Average variance extracted (AVE)*
Commitment	0.92	0.65	0.90	0.74
Cooperation	0.93	0.72	0.96	0.69
Coordination	0.94	0.72	0.87	0.69
Investment	0.92	0.71	0.93	0.53
Satisfaction	0.95	0.77	0.93	0.78
Trust	0.93	0.72	0.90	0.65

Table 5 Structural model relationships

Structural relationships	*PLS-SEM*		*CB-SEM*	
	Beta coefficient	*P-value*	*Beta coefficient*	*P-value*
Commitment → satisfaction	0.26	0.000	0.22	0.000
Cooperation → commitment	0.48	0.000	0.55	0.000
Cooperation → trust	0.58	0.000	0.54	0.000
Coordination → commitment	0.09	0.130	0.05	0.440
Coordination → trust	0.04	0.550	0.19	0.006
Investment → commitment	0.19	0.002	0.10	0.130
Investment → trust	–0.27	0.000	–0.31	0.000
Trust → commitment	0.24	0.002	0.19	0.000
Trust → satisfaction	0.69	0.000	0.75	0.000

The assessment of the significance and relevance of the structural model relationships is shown in Table 5. Of the nine relationships, five beta coefficients are somewhat larger using PLS-SEM while four are larger using CB-SEM, but the coefficients are fairly comparable with only small differences. Using either technique, however, the p values for the coefficients are comparable. As noted earlier, the really meaningful differences are between the loadings on the measurement models, with PLS-SEM results being consistently larger.

The predictive ability of the theoretical structural model is based on the size of the R^2 value. Using the PLS-SEM approach the explained variance is 0.72 for satisfaction, 0.56 for commitment, and 0.34 for trust. Using the CB-SEM approach the explained variance is 0.78 for satisfaction, 0.52 for commitment, and 0.37 for trust. At first glance, the implication is that the CB-SEM approach explained variance results are relatively higher, or at minimum comparable. But remember only the common variance is used with CB-SEM while total variance is used to obtain a solution with PLS-SEM, and only four out of six original indicators were retained in the final CB-SEM model results.

As an example, we will consider the satisfaction construct. Using PLS-SEM, all six of the satisfaction indicators had loadings above the recommended 0.708 and were retained, resulting in an R^2 of 72%. Since the total variance in the six indicators is six, the amount of total variance explained is 4.32 (.72% × 6). Now let's consider the CB-SEM results. Only four of the original six indicators were retained, so if the objective is to predict the total variance in the original six indicators we are starting with only 66% of the original variance. At the same time, with CB-SEM the analysis is based only on the common variance in the indicators, not the total variance. The CB-SEM software does not indicate how much of the total variance is captured in the covariance matrix (i.e., the common variance), but a reasonable assumption is that the common variance in a typical set of indicators is only 70% of the total variance. The result, therefore, is that the solution using CB-SEM in our example is typically obtained with about 70% of the total variance in the retained measured indicators. Based on our example here, the 70% common variance used to represent the four indicators retained in the final model is only 2.8 (70% of four indicators). Since the R2 for the CB-SEM approach is 78%, the amount of variance explained in the original six indicators is 2.184, or 36.4% (78% of 2.8 = 2.184). Considering that the explained variance in the satisfaction construct using PLS-SEM is 72%, compared to only 36.4% for CB-SEM, it is logical to question the extent to which the CB-SEM satisfaction construct actually represents a valid proxy measure of the original satisfaction construct (Hair et al., 2016b).

Table 6 summarises these calculations. If the focus of your research is on prediction of the variance in the dependent variable construct(s), this analysis indicates PLS-SEM is the recommended method. In addition, Becker et al.'s (2012) simulation study provides support for the superior predictive capabilities of PLS-SEM, as do Evermann and Tate's (2016) simulation studies that also indicate PLS-SEM outperforms factor-based SEM in terms of prediction. Based on their results, PLS-SEM enables researchers to specify explanatory, theory-based models to aid in theory development, evaluation, and confirmation.

Table 6 Calculation of CB-SEM explained variance – satisfaction construct

Satisfaction construct – six original indicators	*Variance*
Total variance in six indicators	6
Four indicators retained (CB-SEM) = remaining variance (66%)	4
Common variance in four indicators (assumes 60% of 4)	2.8
CB-SEM explained variance – R^2 = 78% of 2.8	2.184
1.872/6 (total variance in original six indicators)	36.4%

Finally, most GOF measures resulting from the model estimation using CB-SEM meet recommended guidelines, but only after indicator deletion (Table 7). Specifically, the analysis results in a normed Chi-square (X^2, CMIN/DF) of 1.98, which meets recommended guidelines. Also, the CFI is > 0.95 and the RMSEA is < 0.08, both of which meet the recommended guidelines (Hair et al., 2010). But GFI and AGFI are low and problematic.

Table 7 Model fit for CB-SEM method

		Chi-square	*CMIN/DF*	*GFI*	*AGFI*	*CFI*	*RMSEA*
Initial solution	Default model	1,444.68	3.004	0.749	0.707	0.874	0.086
Final solution after indicator deletion	Default model	384.18	1.98	0.889	0.855	0.958	0.060

5 Differences between the two methods

Since CB-SEM and PLS-SEM are different approaches, and have different assumptions, it is important to select the method that is most appropriate for your research. Recommended guidelines, adapted and extended from Hair et al. (2017b), are shown in Table 8. One of the most common reasons for using PLS-SEM has been sample size (Ringle et al., 2012). However, other reasons include prediction (Hair et al., 2011), non-normal data, which is typical of most social science studies (Hair et al., 2014b), complex models and advanced analyses (Hair et al., 2018; Matthews, 2017; Sarstedt et al., 2011b), as well as a desire to identify unobserved heterogeneity (Hair et al., 2016a; Matthews et al., 2016a; Sarstedt et al., 2011a).

Table 8 Guidelines for selecting PLS-SEM and CB-SEM

Types of analysis	*Recommended method*		
	PLS-SEM	*CB-SEM*	*Both*
Objective = prediction	X		
Objective = exploratory research or theory development	X		
Objective = explanation only		X	
Objective = explanation and prediction	X		
Measurement philosophy = total variance (composite-based)	X		
Measurement philosophy = common variance only (factor-based)		X	
Reflective measurement model specification			X
Formative measurement model specification	X		
Metric data			X
Non-metric data = ordinal and nominal	X		
Smaller sample sizes – N = < 100	X		
Larger sample sizes – N = > 100			X
Binary moderators			X
Continuous moderators	X		
Normally distributed data			X
Non-normally distributed data	X		
Secondary (archival) data	X		
Higher order constructs = two 1st order constructs	X		
Higher order constructs = three of more 1st order constructs			X
Latent variable scores needed for subsequent analysis	X		

When deciding whether to use PLS-SEM or CB-SEM, researchers should recognise that PLS-SEM achieves greater statistical power at all sample sizes, but particularly smaller sample sizes, compared to CB-SEM. Greater statistical power means that when using PLS-SEM a specific relationship is more likely to be statistically significant when it is present in the population. The higher statistical power makes PLS-SEM particularly suitable, therefore, for exploratory research where theory is less developed. As Wold (1980) noted, the specification of path models is an evolutionary process. The empirical content of the model is obtained by analysing the data, and the model is improved by interactions through the estimation procedure between the model and the data, as well as researcher input.

6 Conclusions

These are exciting times for social science researchers. Quite a few new methods of analysis are emerging that are very useful in better understanding relationships in data. In this paper we have compared the results of two popular SEM approaches. Both approaches are excellent tools for social sciences researchers. But for the most part they are applicable in different research situations. We have summarised the most important considerations in selecting either CB-SEM or PLS-SEM as your method of analysis.

Our findings summarise the similarities and differences in the assumptions, application, and potential types of analyses when using CB-SEM versus PLS-SEM. If the theory being investigated is well established, and the measurement is effectively executed, then CB-SEM often works well. But CB-SEM assumes normality of data distributions, which is seldom met in social sciences research. In contrast, PLS-SEM is non-parametric and not only works well with non-normal distributions, but also has very few restrictions on the use of ordinal and binary scales, when coded properly. There are alternative approaches to CB-SEM (other than the maximum likelihood algorithm) that are designed to work with non-normal data, but they require large sample sizes. In our example, the CB-SEM method resulted in a substantial loss of indicator variables in an effort to achieve acceptable GOF. At the same time, the PLS-SEM method enabled retention of many more indicator items, which supports both measurement and structural theory development. Finally, comparison of the R^2 output of the two methods indicates that if prediction is the focus of your research, then PLS-SEM is the preferred method because in a direct comparison with CB-SEM the variance explained in the dependent variables is substantially higher. Overall, therefore, the PLS-SEM method is much more appropriate at the theory development stage than is CB-SEM.

Anderson and Gerbing (1988) note that SEM provides researchers with a comprehensive approach for assessing and modifying theoretical models. While CB-SEM was by far the most widely used SEM method until recently (Hair et al., 2017a), the use of PLS-SEM has grown dramatically in recent years (Hair et al., 2017c). Disciplines such as strategic management (Hair et al., 2012a), marketing (Hair et al., 2012b), accounting (Lee et al., 2011), information systems (Ringle et al., 2012; Hair et al., 2017b), family business (Sarstedt et al., 2014b), and tourism (Oom do Valle and Assaker, 2016) have all published articles on the application of PLS-SEM. Overall, SEM approaches in general are preferred in most instances because contributions using this method are more likely to be recommended by reviewers, and hence more likely to be published than papers using other statistical procedures (Babin et al., 2008), and also achieve higher levels of prediction than multiple regression (Lee et al., 2011). Some scholars have been critical of the PLS-SEM method, but for the most part their criticisms are unfounded (Henseler et al., 2014).

The widespread application of second generation statistical methods, such as SEM, does not mean that traditional statistical approaches such as multiple regression or MANOVA are no longer useful, or that their results are meaningless. It is simply the logical evolution of statistical methods, and we encourage social sciences scholars to consider using these newer, more powerful and often more flexible research tools. Indeed, there are many statistical analyses possible with SEM that cannot be completed with the first generation methods. For example, PLS-SEM and the SmartPLS software (Ringle et al., 2015) can facilitate SEM solutions with virtually any level of complexity in the structural model and/or constructs – including higher order constructs that typically reduce multicollinearity problems (Hair et al., 2018), unobserved heterogeneity (Hair et al., 2016a; Matthews et al., 2016a), multi-group analysis (Matthews, 2017), and different algorithms (Sarstedt et al., 2016).

We recommend the use of SEM methods in general, and particularly PLS-SEM, because of the method's ability to obtain meaningful solutions in almost any situation, particularly when small sample sizes are all that is possible, such as business-to-business research, and when the research focuses on complex theoretical models with a large number of indicators as well as numerous endogenous and exogenous constructs, or non-normal data distributions. Finally, being a 'causal-predictive' technique [Jöreskog and Wold, (1982), p.270] PLS-SEM allows combining explanation and prediction perspectives to model estimation, whose joint consideration is the main concern in most of business and social science research in general.

Finally, the comparison of applications of this data to CB-SEM and PLS-SEM is not necessarily meant to be representative of all SEM datasets. It does, however, make scholars aware of a number of important issues that are likely to arise and should be considered in selecting the appropriate SEM method for their research.

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