PLS-SEM: INDEED A SILVER BULLET

Joe F. Hair, Christian M. Ringle, and Marko Sarstedt

Structural equation modeling (SEM) has become a quasi-standard in marketing and management research when it comes to analyzing the cause–effect relations between latent constructs. For most researchers, SEM is equivalent to carrying out covariance-based SEM (CB-SEM). While marketing researchers have a basic understanding of CB-SEM, most of them are only barely familiar with the other useful approach to SEM—partial least squares SEM (PLS-SEM). The current paper reviews PLS-SEM and its algorithm, and provides an overview of when it can be most appropriately applied, indicating its potential and limitations for future research. The authors conclude that PLS-SEM path modeling, if appropriately applied, is indeed a "silver bullet" for estimating causal models in many theoretical models and empirical data situations.

Structural equation modeling (SEM) first appeared in the marketing literature in the early 1980s (e.g., Bagozzi 1994; Bagozzi and Yi 1988; Fornell and Larcker 1981a, 1981b), but in recent years, its application has become quite widespread. Indeed, fewer than ten articles using SEM were published in marketing journals prior to 1990, while more than two-thirds of all articles applying SEM appeared between 1995 and 2007 (Babin, Hair, and Boles 2008).

The desire to test complete theories and concepts is one of the major reasons authors conducting business research—particularly marketing—have embraced SEM (Henseler, Ringle, and Sinkovics 2009; Steenkamp and Baumgartner 2000). For many researchers, SEM is equivalent to carrying out covariance-based SEM (CB-SEM) analyses using software such as Amos, EQS, LISREL, Mplus, and others. But SEM also needs to be thought of as including another unique and very useful approach—partial least squares SEM (PLS-SEM).

PLS-SEM is a causal modeling approach aimed at maximizing the explained variance of the dependent latent constructs. This is contrary to CB-SEM's objective of reproducing the theoretical covariance matrix, without focusing on explained variance. While far less popular than CB-SEM, PLS-SEM has been increasingly applied in marketing and other business disciplines (e.g., Henseler, Ringle, and Sinkovics 2009), with more than 100 published studies featuring PLS-SEM in the top 20 marketing journals (for the marketing journal ranking, see Hult, Reimann, and Schilke 2009).

Despite the growing number of studies on PLS-SEM, some scholars view the method as less rigorous and therefore less suitable for examining relationships between latent variables. A likely reason for these less favorable perceptions is individual author's previous experience and familiarity with the CB-SEM approach and software that match the needs of certain disciplines (e.g., psychology). Another is that few researchers viewed PLS-SEM as a "silver bullet" or panacea for dealing with empirical research challenges such as smaller sample sizes (Marcoulides and Saunders 2006; Sosik, Kahai, and Piovoso 2009). These negative perceptions of PLS-SEM are unfortunate and shortsighted. When properly applied, the method has many benefits not offered by CB-SEM.

CB-SEM develops a theoretical covariance matrix based on a specified set of structural equations. The technique focuses on estimating a set of model parameters in such a way that the difference between the theoretical covariance matrix and the estimated covariance matrix is minimized (e.g., Rigdon 1998). The CB-SEM model estimation requires a set of assumptions to be fulfilled, including the multivariate normality of data, minimum sample size, and so forth (e.g., Diamantopoulos and Siguaw 2000). But if CB-SEM assumptions cannot be met, or the research objective is prediction rather than confirmation of structural relationships, then variance-based PLS-SEM is the preferred method. In comparison with CB-SEM results, which can be highly

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imprecise when the assumptions are violated, PLS-SEM often provides more robust estimations of the structural model (e.g., Lohmöller 1989; Reinartz, Haenlein, and Henseler 2009; Ringle et al. 2009; Wold 1982).

This paper provides insights into PLS-SEM's current state of the art by merging contributions from the marketing, statistics, and management disciplines. The overall objective is to encourage the appropriate use of PLS-SEM in empirical research by describing the method's strengths while at the same time highlighting potentially problematic issues. Thus, we call for a more balanced and informed perspective of PLS-SEM's application in marketing and related disciplines.

STRUCTURAL EQUATION MODELING OVERVIEW

Path analysis models were first developed by Sewall Wright (1921), a biostatistician, in the early 1920s. Structural models as applied in the social sciences only began appearing in the 1970s (Bollen 1989; Jöreskog 1973) with their increasing application paralleling the availability of software (Arbuckle 2010; Bentler 1995; Jöreskog and Sörbom 1996), all of which executed CB-SEM. While Herman Wold—who was also the academic advisor of Karl Jöreskog, one of the LISREL CB-SEM software package developers—originated variance-based SEM in the 1970s (Wold 1973, 1975), software packages executing PLS-SEM were developed much later (e.g., SmartPLS; Ringle, Wende, and Will 2005).

Jöreskog and Wold (1982) viewed CB-SEM and PLS-SEM as complementary rather than competitive statistical methods. More specifically, Wold (1982) recognized CB-SEM's potential for the social sciences but was concerned about the informational and distributional requirements that he regarded as unrealistic for empirical research. He also believed that estimation and description were emphasized too much and prediction too little (Dijkstra 2010). It is important to note that next to PLS-SEM, another PLS culture has arisen from Wold's original works—PLS regression. This approach generalizes and combines features from principal component analysis and multiple regression but generally does not allow for the evaluation of complex cause–effect relationships between latent constructs (for a notable exception, see Arteaga, Gallarza, and Gil 2010). Natural science disciplines, such as chemometrics, generally use PLS regression (e.g., Wold, Sjöström, and Eriksson 2001), but PLS-SEM is the approach that has become established in marketing and business research (e.g., Fornell and Bookstein 1982; Henseler, Ringle, and Sinkovics 2009).

The philosophical distinction between CB-SEM and PLS-SEM is straightforward. If the research objective is theory testing and confirmation, then the appropriate method is CB-SEM. In contrast, if the research objective is prediction and theory development, then the appropriate method is PLS-SEM. Conceptually and practically, PLS-SEM is similar to using multiple regression analysis. The primary objective is to maximize explained variance in the dependent constructs but additionally to evaluate the data quality on the basis of measurement model characteristics. Given PLS-SEM's ability to work efficiently with a much wider range of sample sizes and increased model complexity, and its less restrictive assumptions about the data, it can address a broader range of problems than CB-SEM. Moreover, because the constructs' measurement properties are less restrictive with PLS-SEM, constructs with fewer items (e.g., one or two) can be used than those that CB-SEM requires. Overall, when measurement or model properties restrict the use of CB-SEM or when the emphasis is more on exploration than confirmation, PLS-SEM is an attractive alternative to CB-SEM and often more appropriate.

While PLS-SEM can be applied to a wider range of situations, researchers must always be aware of the differences in interpretation of the results, particularly as they relate to the constructs' measurement properties. For example, can PLS-SEM be appropriately applied when a measurement theory fails to meet the confirmatory factor analysis's criteria, including convergent validity and discriminant validity tests? PLS-SEM estimates loadings of the indicator variables for the exogenous constructs based on their prediction of the endogenous constructs, not their shared variance among indicator variables on the same construct. Thus, the loadings in PLS-SEM are in a way their contribution to the path coefficients. Hair et al. (2010) give a numerical example with a prespecified covariance matrix to highlight the differences between the two methods. While CB-SEM provides poor results for the measurement model but a significant structural model relationship, PLS-SEM offers acceptable results for the measurement models whereas the structural model relationship is not significant. On the contrary, Tenenhaus (2008) offers an example in which PLS-SEM and CB-SEM results are in close correspondence. Both examples show that the differences in results are primarily a matter of measurement model quality. Using "good" measures and data, both approaches practically yield the same results. As a consequence, a case whether the one or the other methods is better should not be made, especially because the majority of prior studies comparing CB-SEM and PLS-SEM did not explicitly control for CB-SEM specification biases, which is an important issue in order to conduct a meaningful comparison of the two approaches.

To correctly apply CB-SEM and PLS-SEM, researchers must understand the purposes for which each approach was developed and apply them accordingly. Structural equation models with good measurement properties generally achieve comparable results with either approach, especially when the CB-SEM's model specifications have been correctly set up (Reinartz, Haenlein, and Henseler 2009). Moreover, both approaches should still consider issues such as the appropriate use and interpretation of formative versus reflective measures (Diamantopoulos, Riefler, and Roth 2008). These situations are often the ones in which the measurement properties are questionable and the results may diverge, thus requiring the researcher to make a reasoned judgment as to which approach is most appropriate.

The PLS-SEM Algorithm

A structural equation model with latent constructs has two components. The first component is the structural model—typically referred to as the *inner model* in the PLS-SEM context—which shows the relationships (paths) between the latent constructs. PLS-SEM only permits recursive relationships in the structural model (i.e., no causal loops). Therefore, the structural paths between the latent constructs can only head in a single direction. In the structural model, we distinguish between exogenous and endogenous constructs. The term *exogenous* is used to describe latent constructs that do not have any structural path relationships pointing at them. Thus, the term *endogenous* describes latent target constructs in the structural model that are explained by other constructs via structural model relationships.

The second component of the structural equation model comprises the measurement models, also referred to as *outer models* in the PLS-SEM context. The measurement models include the unidirectional predictive relationships between each latent construct and its associated observed indicators (Figure 1). Multiple relations are not permitted, therefore indicator variables are associated with only a single latent construct. PLS-SEM can handle both formative and reflective measurement models. Reflective indicators are seen as functions of the latent construct, and changes in the latent construct are reflected in changes in the indicator (manifest) variables. Reflective indicators are represented as single-headed arrows pointing from the latent construct outward to the indicator variables; the associated coefficients for these relationships are called *outer loadings* in PLS-SEM. In contrast, formative indicators are assumed to cause a latent construct, and changes in the indicators determine changes in the value of the latent construct (Diamantopoulos and Winklhofer 2001; Diamantopoulos, Riefler, and Roth 2008). Formative indicators are represented by single-headed arrows pointing toward the latent construct inward from the indicator variables; the associated coefficients for these formative relationships are called *outer weights* in PLS-SEM. Researchers using PLS-SEM often refer to reflective measurement models (i.e., scales) as Mode A, and formative measurement models (i.e., indices) are labeled Mode B (e.g., Rigdon, Ringle, and Sarstedt 2010).

Figure 1 shows an example of a simple path model. The model has a single endogenous (dependent) latent construct (Y_3) and two exogenous (independent) latent constructs (Y_1 and Y_2), which are indicated as ovals. The differentiation between endogenous and exogenous constructs is clear-cut in this PLS-SEM example. However, if a fourth latent construct (Y_4) were included in the SEM model with a relationship from Y_3 to Y_4, both latent constructs would be described as endogenous. The latent constructs Y_1 and Y_2 are measured with two formative indicator variables each, indicated as boxes (X_1 to X_4, with arrows pointing toward the constructs). On the contrary, Y_3 is measured with three reflective indicator variables (X_5 to X_7, with arrows pointing away from the construct). Most theoretical constructs (especially formative ones) will be measured by six or seven indicator variables, but our example includes fewer indicators to facilitate the presentation.

The basic PLS-SEM algorithm (Lohmöller 1989) follows a two-stage approach. In the first stage, the latent constructs' scores are estimated via a four-step process as shown in Table 1. The second stage calculates the final estimates of the outer weights and loadings as well as the structural model's path coefficients. The path modeling procedure is called *partial* because the iterative PLS-SEM algorithm estimates the coefficients for the partial ordinary least squares regression models in the measurement models and the structural model. More specifically, when a formative measurement model is assumed, a multiple regression model is estimated with the latent construct as the dependent variable and the assigned indicators as independent variables (computation of outer weights). In contrast, when a reflective measurement model is assumed, the regression model includes single regressions with each indicator individually being the dependent variable, whereas the latent construct is always the independent variable (computation of outer loadings). When the structural model relationships are calculated, each endogenous latent construct represents the dependent variable with its latent construct antecedents as independent variables in a partial

Figure 1
Path Model Example

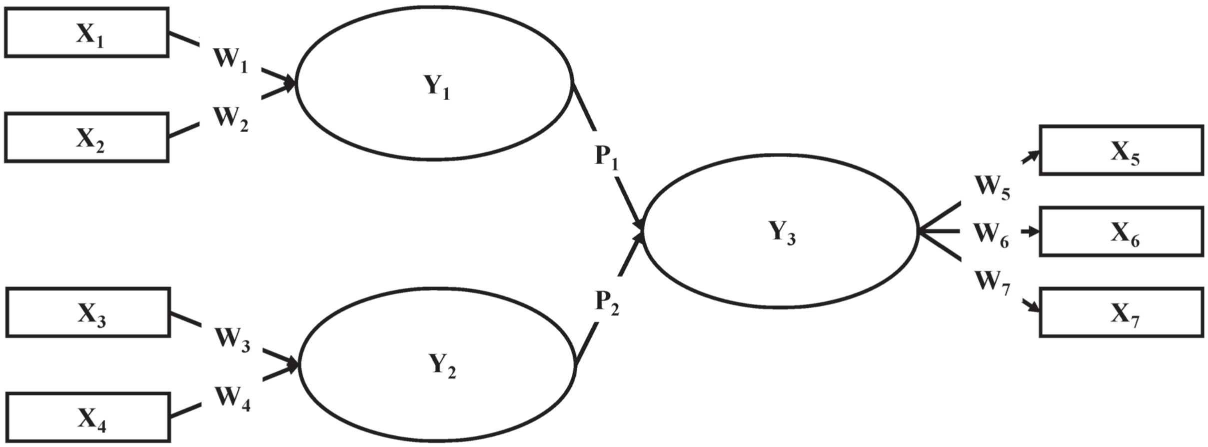

Table 1
Stages and Steps in Calculating the Basic PLS-SEM Algorithm

Stage One: Iterative estimation of latent construct scores
Step 1: Outer approximation of latent construct scores (the scores of Y_1, Y_2, and Y_3 are computed based on the manifest variables' scores and the outer coefficients from Step 4)
Step 2: Estimation of proxies for structural model relationships between latent constructs (P_1 and P_2)
Step 3: Inner approximation of latent construct scores (based on scores for Y_1, Y_2, and Y_3 from Step 1 and proxies for structural model relationships, P_1 and P_2, from Step 2)
Step 4: Estimation of proxies for coefficients in the measurement models (the relationships between indicator variables and latent constructs with scores from Step 3; W_1 to W_7)
Stage Two: Final estimates of coefficients (outer weights and loadings, structural model relationships) are determined using the ordinary least squares method for each partial regression in the PLS-SEM model.

regression model. All partial regression models are estimated by the iterative procedures of the PLS-SEM algorithm.

Stage One has four steps. In Step 1 of Stage One, the latent construct scores' outer proxies are computed as linear combinations of the values of all (standardized) indicators associated with a particular latent construct. For example, values of X_1 and X_2 are used to compute the proxy score for the latent construct Y_1. Later iterations use the estimated coefficients of the paths (e.g., W_1 and W_2 for Y_1, whereby W represents the outer weight or loading coefficient; for the simplicity of representation in this example, we do not use different symbols for the Mode A and Mode B measurement models) between the latent constructs and the indicator variables from Step 4 of Stage One. For the initial iteration, any combination of indicators can serve as a proxy for the latent construct. PLS-SEM software programs, such as SmartPLS (Ringle, Wende, and Will 2005), use a uniform value of 1 as an initial value for each of the outer weights (W_1 to W_7).

In Step 2, the PLS-SEM algorithm computes proxies for the structural model relationships (P_1 and P_2). Several different weighting schemes are available to estimate these proxies. We recommend applying the path weighting scheme that uses combinations of regression analyses and bivariate correlations based on latent construct scores as proxies for structural model relationships. This method develops latent construct scores that maximize the final R^2 value estimations of the endogenous latent constructs (Lohmöller 1989). In Step 3, the inner proxies of the latent construct scores (Y_1, Y_2, and Y_3) are calculated as linear combinations of their respective adjacent latent construct outer proxies (from Step 1) using the previously determined (Step 2) inner weights. Finally, in Step 4, the outer weights (W_1 to W_7) are calculated in two different ways, depending on the type of measurement model represented by each construct. If a construct is measured reflectively, then the correlations between the inner proxy of each latent construct and its indicator variables are applied (outer loadings). If a construct is measured formatively, then regression weights (i.e., outer weights) are applied that are the result of the ordinary least squares regression of each latent construct's inner proxy on its indicator variables.

The four steps in Stage One are repeated until the sum of the outer weights' changes between two iterations is sufficiently low. That is, the sum of the changes drops below a predetermined limit. The recommended predetermined limit is a threshold value of 10^{-5} to ensure the PLS-SEM algorithm's convergence while simultaneously minimizing computational requirements. If the algorithm converges in Step 4 of Stage One, then the final outer weights are used to compute the final latent construct scores in Stage Two. The final latent construct scores are used to run the ordinary least squares regressions for each construct to determine the structural model relationships' estimates (path coefficients). Most PLS-SEM software packages (e.g., SmartPLS) provide a graphical user interface to create the model and implement the basic PLS algorithm for model estimation.

CHOOSING PLS-SEM VERSUS CB-SEM

PLS-SEM is a promising method that offers vast potential for SEM researchers especially in the marketing and management information systems disciplines. PLS-SEM is, as the name implies, a more "regression-based" approach that minimizes the residual variances of the endogenous constructs. Compared to CB-SEM, it is more robust with fewer identification issues, works with much smaller as well as much larger samples, and readily incorporates formative as well as reflective constructs.

These advantages are constrained by some disadvantages. One disadvantage is PLS-SEM's focus is on maximizing partial model structures. Specifically, the PLS-SEM algorithm first optimizes measurement model parameters and then, in a second step, estimates the path coefficients in the structural model. Thus, researchers applying PLS-SEM first have to examine the measurement models' characteristics and deal with those that are unacceptable. If this approach is followed, PLS-SEM findings can be interpreted after assessment of the model's measurement characteristics—similar to CB-SEM methods. Another issue that restricts the use of PLS-SEM for theory testing and confirmation is that there is no adequate global measure of goodness of model fit. In addition, it should be noted that, in general, PLS-SEM parameter estimates are not optimal regarding bias and consistency—a property frequently referred to as *PLS-SEM bias.* Although the CB-SEM versus PLS-SEM discussion strongly emphasizes this characteristic, simulation studies show that the differences between CB-SEM and PLS-SEM estimates are at very low levels (e.g., Reinartz, Haenlein, and Henseler 2009). Thus, the extensively discussed PLS-SEM bias is often of minor relevance for practical applications because estimates will be asymptotically correct under consistency at large conditions (i.e., both a large sample size and large numbers of indicators per latent variable) (Jöreskog and Wold 1982).

Furthermore, although the estimates that result from PLS-SEM are, on average, biased, they also exhibit a lower degree of variability than those produced by CB-SEM (e.g., Reinartz, Haenlein, and Henseler 2009; Ringle et al. 2009). This important feature holds especially for research situations in which maximum likelihood–based CB-SEM typically exhibits inflated standard errors (Sosik, Kahai, and Piovoso 2009) and the method's premises are violated (e.g., small sample size, nonnormal data, high model complexity). This increased efficiency in parameter estimation is manifested in PLS-SEM's greater statistical power than that of CB-SEM.

The choice of either PLS-SEM or CB-SEM is determined by the relevant research's objective. In causal modeling situations where prior theory is strong and further testing and confirmation are the goals, CB-SEM is the more appropriate statistical methodology. Global goodness-of-fit criteria that also emphasize theory testing rather than theory building can be used to assess CB-SEM results (Anderson and Gerbing 1988). However, like all statistical methods, CB-SEM has shortcomings. For example, CB-SEM approaches largely ignore the prediction objective. If the structural relationships between the latent constructs are the primary concern in theory testing, researchers are generally less concerned with predictive accuracy. In situations where theory is less developed, however, researchers need an alternative approach to examine structural models if the primary objective is not theory confirmation. Thus, because of its prediction orientation, PLS-SEM is the preferred method when the research objective is theory development and prediction.

Moreover, PLS-SEM avoids the indeterminacy problem (difficulty with estimating stable factor scores) and develops more precise estimates of factor scores (Fornell 1982) as the algorithm calculates latent variable scores as exact linear combinations of the observed indicator variables. As a consequence, PLS-SEM is particularly useful when subsequent analyses employ these scores. For example, PLS-SEM impact-performance analyses (e.g., Höck, Ringle, and Sarstedt 2010; Völckner et al. 2010), which enable researchers to easily prioritize activities for potential improvements and render the required managerial decisions, make use of latent variable scores. Likewise, researchers have used differences in latent construct scores to evaluate experimental setups (e.g., Schwaiger, Sarstedt, and Taylor 2010).

CB-SEM and PLS-SEM methodologies differ from a statistical point of view, but PLS-SEM estimates can be good proxies of CB-SEM results. For example, when CB-SEM assumptions are violated with regard to normality of distributions, minimum sample size, and maximum model complexity, or when related methodological matters emerge, such as Heywood cases and inflated parameter estimates' standard errors (Rindskopf 1984), PLS-SEM is a good

Table 2
Rules of Thumb for Selecting CB-SEM or PLS-SEM

Research Goals

- If the goal is predicting key target constructs or identifying key "driver" constructs, select PLS-SEM.
- If the goal is theory testing, theory confirmation, or comparison of alternative theories, select CB-SEM.
- If the research is exploratory or an extension of an existing structural theory, select PLS-SEM.

Measurement Model Specification

- If formative constructs are part of the structural model, select PLS-SEM.
  Note that formative measures can also be used with CB-SEM but to do so requires accounting for relatively complex and limiting specification rules.
- If error terms require additional specification, such as covariation, select CB-SEM.

Structural Model

- If the structural model is complex (many constructs and many indicators), select PLS-SEM.
- If the model is nonrecursive, select CB-SEM.

Data Characteristics and Algorithm

- If your data meet the CB-SEM assumptions exactly, for example, with respect to the minimum sample size and the distributional assumptions, select CB-SEM; otherwise, PLS-SEM is a good approximation of CB-SEM results.
- *Sample size considerations:*
  - If the sample size is relatively low, select PLS-SEM. With large data sets, CB-SEM and PLS-SEM results are similar, provided that a large number of indicator variables are used to measure the latent constructs (consistency at large).
  - PLS-SEM minimum sample size should be equal to the larger of the following: (1) ten times the largest number of formative indicators used to measure one construct or (2) ten times the largest number of structural paths directed at a particular latent construct in the structural model.
- If the data are to some extent nonnormal, use PLS-SEM; otherwise, under normal data conditions, CB-SEM and PLS-SEM results are highly similar, with CB-SEM providing slightly more precise model estimates.
- If CB-SEM requirements cannot be met (e.g., model specification, identification, nonconvergence, data distributional assumptions), use PLS-SEM as a good approximation of CB-SEM results.
- CB-SEM and PLS-SEM results should be similar. If not, check the model specification to ensure that CB-SEM was appropriately applied. If not, PLS-SEM results are a good approximation of CB-SEM results.

Model Evaluation

- If you need to use latent variable scores in subsequent analyses, PLS-SEM is the best approach.
- If your research requires a global goodness-of-fit criterion, then CB-SEM is the preferred approach.
- If you need to test for measurement model invariance, use CB-SEM.

methodological alternative for theory testing. Another attractive feature for theory testing is PLS-SEM's higher levels of statistical power compared to CB-SEM. Thus, researchers should consider both CB-SEM and PLS-SEM when selecting the appropriate statistical method. Table 2 displays rules of thumb that can be applied when deciding whether to use CB-SEM or PLS-SEM. The rules of thumb are listed according to five types of decision considerations.

WHAT TO LOOK FOR AFTER RUNNING PLS-SEM

Just like any multivariate analysis technique (Hair et al. 2010), applying PLS-SEM requires a thorough assessment of the final results (model evaluation). In many respects, model evaluation in PLS-SEM is still heavily influenced by CB-SEM reporting—especially in terms of the evaluation of measurement models—because it follows the notion of an underlying covariance-based latent construct–generating mechanism.

PLS-SEM assessment typically follows a two-step process that involves separate assessments of the measurement models and the structural model. The first step is to examine the measures' reliability and validity according to certain criteria associated with formative and reflective measurement model specification. This first step is based on the logic that if you are not confident that the measures represent the constructs of interest, there is little reason to use them to examine the structural relationships. If the measures are shown to be adequate, however, the second step involves an assessment of the structural model estimates. As in any statistical analysis, the evaluation of the measurement and structural models should include examining the parameter estimates' stability by means of a holdout sample. Generally, we recommend using 30 percent of the original sample as the holdout sample. However, researchers must consider the minimum sample size requirements as described in Table 2.

In the following, we provide an overview of aspects related to the evaluation of the measurement models and

Table 3
Rules of Thumb for Model Evaluation

Reflective Measurement Models
- Internal consistency reliability: Composite reliability should be higher than 0.70 (in exploratory research, 0.60 to 0.70 is considered acceptable).
- Indicator reliability: Indicator loadings should be higher than 0.70.
- Convergent validity: The average variance extracted (AVE) should be higher than 0.50.
- Discriminant validity:
  - The AVE of each latent construct should higher than the construct's highest squared correlation with any other latent construct (Fornell–Larcker criterion).
  - An indicator's loadings should be higher than all of its cross loadings.

Formative Measurement Models
- Examine each indicator's weight (relative importance) and loading (absolute importance) and use bootstrapping to assess their significance. The minimum number of bootstrap samples is 5,000, and the number of cases should be equal to the number of observations in the original sample. Critical *t*-values for a two-tailed test are 1.65 (significance level = 10 percent), 1.96 (significance level = 5 percent), and 2.58 (significance level = 1 percent).
  - When all the indicator weights are significant, there is empirical support to keep all the indicators.
  - If both the weight and loading are nonsignificant, there is no empirical support to retain the indicator and its theoretical relevance should be questioned.
- Multicollinearity: Each indicator's variance inflation factor (VIF) value should be less than 5.
- Indicator weights should be examined to determine if they are affected by (observed or unobserved) heterogeneity, which results in significantly different group-specific coefficients. If theory supports the existence of alternative groups of data, carry out PLS-SEM multigroup or moderator analyses. If no theory or information is available about the underlying groups of data, an assessment of unobserved heterogeneity's existence must be conducted by means of the finite mixture PLS (FIMIX-PLS) method.
- When many indicators are used to measure a formative construct, with some being nonsignificant, establish two or more distinct constructs, provided there is theoretical support for this step.

Structural Model
- R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables in the structural model can be described as substantial, moderate, or weak, respectively.
- Use bootstrapping to assess the path coefficients' significance. The minimum number of bootstrap samples is 5,000, and the number of cases should be equal to the number of observations in the original sample. Critical *t*-values for a two-tailed test are 1.65 (significance level = 10 percent), 1.96 (significance level = 5 percent), and 2.58 (significance level = 1 percent).
- Predictive relevance: Use blindfolding to obtain cross-validated redundancy measures for each construct. Make sure the number of valid observations is not a multiple integer number of the omission distance *d*. Choose values of *d* between 5 and 10.
  Resulting Q^2 values of larger than zero indicate that the exogenous constructs have predictive relevance for the endogenous construct under consideration.
- Heterogeneity: If theory supports the existence of alternative groups of data, carry out PLS-SEM multigroup or moderator analyses. If no theory or information about the underlying groups of data is available, an assessment of unobserved heterogeneity's existence must be conducted by means of the FIMIX-PLS method, which is available in the SmartPLS software package.

the structural model. In addition, we address the frequently asked question: Why does PLS-SEM rely on bootstrapping? We summarize the rules of thumb for model evaluation in Table 3. Researchers and practitioners can conduct all the analyses proposed in this section by using the SmartPLS (Ringle, Wende, and Will 2005) software package.

Evaluation of Measurement Models

We must distinguish between reflective and formative measurement models to evaluate them (Henseler, Ringle, and Sinkovics 2009). Reflective measurement models should be assessed with regard to their reliability and validity. Construct reliability assessment routinely focuses on composite reliability as an estimate of a construct's internal consistency. Unlike Cronbach's alpha, composite reliability does not assume that all indicators are equally reliable, making it more suitable for PLS-SEM, which prioritizes indicators according to their reliability during model estimation. Composite reliability values of 0.60 to 0.70 in exploratory research and values from 0.70 to 0.90 in more advanced stages of research are regarded as satisfactory (Nunnally and Bernstein 1994), whereas values below 0.60 indicate a lack of reliability. Likewise, each indicator's reliability needs to be taken into account, whereby each indicator's absolute standardized loading should be higher than 0.70. Generally, indicators with loadings between 0.40 and 0.70 should only be considered for removal from the scale if deleting this indicator leads to an increase in composite reliability above the suggested threshold value. Another consideration in the decision to delete indicators is the extent to which their removal affects validity. Weaker indicators are sometimes retained on the basis of their contribution to content validity. Indicators that exhibit very low loadings of 0.40 and lower should, however, always be eliminated from reflective scales.

Reflective measurement models' validity assessment focuses on convergent validity and discriminant validity. For convergent validity, researchers need to examine the average variance extracted (AVE). An AVE value of 0.50 and higher indicates a sufficient degree of convergent validity, meaning that the latent variable explains more than half of its indicators' variance. For the assessment of discriminant validity, two measures have been put forward—the Fornell–Larcker criterion and cross loadings. The Fornell–Larcker criterion (Fornell and Larcker 1981a) postulates that a latent construct shares more variance with its assigned indicators than with another latent variable in the structural model. In statistical terms, the AVE of each latent construct should be greater than the latent construct's highest squared correlation with any other latent construct. The second criterion of discriminant validity is usually a bit more liberal: an indicator's loading with its associated latent construct should be higher than its loadings with all the remaining constructs (i.e., the cross loadings).

Traditional statistical evaluation criteria for reflective scales cannot be directly transferred to formative indices. In a formative measurement model, indicators represent the latent construct's (potentially) independent causes and thus do not necessarily correlate highly. Furthermore, formative indicators are assumed to be error free (Edwards and Bagozzi 2000). Consequently, the concepts of internal consistency reliability and convergent validity are not meaningful when formative indicators are involved. Instead, theoretical rationale and expert opinion play a more important role in the evaluation of formative indexes. Nevertheless, PLS-SEM also offers some statistical criteria for assessing formative measurement models' quality.

At the indicator level, the question arises whether each indicator indeed contributes to forming the index in accordance with its intended contents. Two specific issues require a critical analysis and careful decisions with respect to the index's contents. First, an indicator that was theorized to contribute to a formative index can be irrelevant. The bootstrapping procedure allows the significance of formative indicators' coefficients to be tested. In addition to considering the significance of the indicator's weight, researchers should also evaluate an indicator's absolute importance for its construct (i.e., the loading). When both weight and loading are nonsignificant, there is no empirical support for the indicator's relevance in providing content to the formative index (Cenfetelli and Bassellier 2009). Researchers must then decide whether to retain or delete a nonsignificant indicator, which is always crucial for the theoretical underpinnings and interpretation of empirical results. If the theory-driven conceptualization of the measure strongly supports the indicator's inclusion (e.g., by means of face, expert, and content validity), it should be kept in the formative measurement model and the researcher should focus on explaining the empirical outcome. However, the researcher can also interpret the empirical finding as countering the conceptual foundations that support the indicator's inclusion and thus decide to exclude the nonsignificant indicator from further analysis. Even though this step usually has almost no effect on the parameter estimates when reestimating the model, one has to bear in mind that eliminating formative indicators can have adverse consequences for the derived measure's content validity (Diamantopoulos and Siguaw 2006).

While nonsignificant indicators may simply imply a lack of theoretical relevance, another potential reason for their lack of significance may be the existence of heterogeneous data structures. If parameter estimates are affected by heterogeneity, a formative indicator may not be significant when solely evaluated on the aggregate data level. But there may be one or more subpopulation(s) in which an indicator is significantly related to the construct while this is not the case in another subpopulation. Therefore, researchers should examine whether heterogeneity affects the coefficients in formative measurement models significantly before eliminating nonsignificant indictors. This can be done by either partitioning the data on the basis of a priori information (e.g., demographic variables; Rigdon, Ringle, and Sarstedt 2010) and estimating distinct models or by using the finite mixture PLS (FIMIX-PLS) method (Ringle, Wende, an Will 2010), which is part of the SmartPLS software package.

Second, an indicator's information can become redundant due to high levels of multicollinearity in the formative measurement model which can cause indicators to be nonsignificant. To determine redundancy, researchers should examine the degree of multicollinearity in the formative indicators (Cassel, Hackl, and Westlund 1999; Diamantopoulos and Winklhofer 2001; Grewal, Cote, and Baumgartner 2004), for instance, by calculating the variance inflation factor (VIF). In the context of PLS-SEM, a VIF value of 5—which implies that 80 percent of an indicator's variance is accounted for by the remaining formative indicators related to the same construct—indicates potential multicollinearity problems. This necessitates the reconsideration of the formative measurement model setup. In light of the discussion above, we recommend eliminating an indicator to relax multicollinearity problems (1) if the level of multicollinearity is very high (as indicated by a VIF value of 5 or higher), (2) if this indicator's formative measurement model coefficient (outer weight) is not significantly different from zero, and (3) the remaining indicators sufficiently capture the domain of the construct under consideration.

It is important to note that the higher number of indicators used to measure a formative latent construct, the more likely it is that one or more indicators will have low or even nonsignificant weights. If this is the case, indicators should be grouped into two or more distinct constructs, provided there is theoretical support for this step (Cenfetelli and Bassellier 2009).

Evaluation of the Structural Model

The primary evaluation criteria for the structural model are the R^2 measures and the level and significance of the path coefficients. Because the goal of the prediction-oriented PLS-SEM approach is to explain the endogenous latent variables' variance, the key target constructs' level of R^2 should be high. The judgment of what R^2 level is high depends, however, on the specific research discipline. Whereas R^2 results of 0.20 are considered high in disciplines such as consumer behavior, R^2 values of 0.75 would be perceived as high in success driver studies. In marketing research studies, R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables in the structural model can, as a rule of thumb, be described as substantial, moderate, or weak, respectively.

The individual path coefficients of the PLS structural model can be interpreted as standardized beta coefficients of ordinary least squares regressions. Just as with the indicators' weights and loadings, each path coefficient's significance can be assessed by means of a bootstrapping procedure. Paths that are nonsignificant or show signs contrary to the hypothesized direction do not support a prior hypothesis, whereas significant paths showing the hypothesized direction empirically support the proposed causal relationship.

Another assessment of the structural model involves the model's capability to predict. The predominant measure of predictive relevance is the Stone–Geisser's Q^2 (Geisser 1974; Stone 1974), which postulates that the model must be able to adequately predict each endogenous latent construct's indicators. The Q^2 value is obtained by using a blindfolding procedure, a sample reuse technique that omits every dth data point part and uses the resulting estimates to predict the omitted part. It is important to note that the omission distance d must be chosen so that the number of valid observations divided by d is not an integer. Experience shows that d values between 5 and 10 are advantageous. The blindfolding procedure is only applied to endogenous latent constructs that have a reflective measurement model specification. Q^2 comes in two forms—the cross-validated redundancy and communality. We recommend using the cross-validated redundancy, which—unlike the cross-validated communality—uses the PLS-SEM estimates of both the structural model and the measurement models for data prediction and, thereby, perfectly fits the PLS-SEM approach. If an endogenous construct's cross-validated redundancy measure value (i.e., Q^2) for a certain endogenous latent variable is larger than zero, its explanatory latent constructs exhibit predictive relevance.

Another important aspect of structural model evaluation is heterogeneity of observations, which can be a threat to the PLS-SEM results' validity, that is, different population parameters are likely to occur for different subpopulations such as segments of consumers, firms, or countries. Consequently, researchers should consider potential sources of heterogeneity and test these by means of multigroup comparison or moderator analyses (Rigdon, Ringle, and Sarstedt 2010). However, the true sources of heterogeneity can never be fully known a priori. As a result, situations arise in which differences are related to unobserved heterogeneity and cannot be attributed to any predetermined variable(s). Several tools for dealing with unobserved heterogeneity within PLS-SEM have recently been developed, with many new approaches appearing only in specialized literature devoted to PLS-SEM methods. Among these, FIMIX-PLS (Hahn et al. 2002; Sarstedt and Ringle 2010) is to date regarded as the primary approach and has become mandatory for evaluating PLS path modeling results (Sarstedt 2008). Using this technique, researchers can either confirm that their results are not distorted by unobserved heterogeneity or they can identify thus far neglected variables that describe the uncovered data segments. Sarstedt et al. (2011) provide a further discussion of the FIMIX-PLS approach, and Ringle, Sarstedt, and Mooi (2010) illustrate its application via the American customer satisfaction index model.

Why PLS-SEM Uses Bootstrapping

PLS-SEM does not presume that the data are normally distributed. Consequently, PLS applies nonparametric bootstrapping (Davison and Hinkley 1997; Efron and Tibshirani 1993), which involves repeated random sampling with replacement from the original sample to create a bootstrap sample, to obtain standard errors for hypothesis testing. The process assumes that the sample distribution is a reasonable representation of the intended population distribution. The bootstrap sample enables the estimated coefficients in PLS-SEM to be tested for their significance (Henseler, Ringle, and Sinkovics 2009).

The procedure creates a large, prespecified number of bootstrap samples (e.g., 5,000) by randomly drawing cases with replacement from the original sample. Each bootstrap sample should have the same number of cases as the original sample. The PLS algorithm estimates the SEM results from each bootstrap sample (e.g., 5,000 PLS-SEM estimations). The repeated bootstrap parameter estimates are then used to create an empirical sampling distribution for each model parameter, and the empirical sampling distribution's standard deviation is used as proxy for the empirical standard error for the parameter. The obtained path model coefficients form a bootstrap distribution, which can be viewed as an approximation of the sampling distribution. The PLS-SEM results of all the bootstrap samples provide the standard error for each path model coefficient. With this information, a student's *t*-test can be performed to measure the significance of path model relationships.

The bootstrapping analysis allows for the statistical testing of the hypothesis that a coefficient equals zero (null hypothesis) as opposed to the alternative hypothesis that the coefficient does not equal zero (two-tailed test). The effectiveness of the bootstrap depends on the sample's representativeness in terms of the targeted population.

SUMMARY AND CONCLUSIONS

PLS-SEM path modeling can indeed be a "silver bullet" for estimating causal models in many theoretical model and empirical data situations. Other researchers' criticisms of PLS-SEM often focus on past abuses instead of on the method's true potential. Researchers must understand the goal of the analysis in order to select an appropriate statistical method for SEM applications.

Instead of using the model to explain the covariation between all the indicators, PLS-SEM provides parameter estimates that maximize the explained variance (R^2 values) of the dependent constructs. The method therefore supports prediction-oriented goals (i.e., explaining/predicting the target constructs in the structural model). Its flexibility (i.e., almost no limiting assumptions regarding the model specifications and data) and its comparatively high statistical power make the PLS method particularly adequate for SEM applications that aim at prediction or theory building such as in studies that focus on identifying critical success drivers (e.g., Höck and Ringle 2010; Sarstedt and Schloderer 2010; Sattler et al. 2010). Finally, PLS-SEM can also be used for confirmatory theory testing.

Recent PLS-SEM research reveals that the method is developing rapidly and has demonstrated numerous technical advancements. These include different approaches to response-based clustering such as FIMIX-PLS (Hahn et al. 2002; Ringle, Sarstedt, and Mooi 2010; Sarstedt and Ringle 2010), PLS genetic algorithm segmentation (Ringle and Schlittgen 2007), and response-based unit segmentation in PLS (REBUS-PLS) (Esposito Vinzi et al. 2008). These methods have been constantly advanced, for example, by addressing model selection issues in FIMIX-PLS (Sarstedt et al. 2011) and comparing several of the approaches by means of computational experiments (Esposito Vinzi et al. 2007; Ringle, Sarstedt, and Schlittgen 2010). The confirmatory tetrad analysis in PLS path modeling (CTA-PLS), as proposed by Gudergan et al. (2008), allows the empirical testing of the measurement models' mode ex post. More specifically, the method tests the null hypothesis of a reflective measurement model. Furthermore, in case of rejection, the method provides support for using the formative measurement model alternative. Other studies broach the issue of moderating effects (Henseler and Chin 2010; Henseler and Fassott 2010), hierarchical component models (Wetzels, Odekerken-Schroder, and van Oppen 2009), and higher-order interaction effects in hierarchical component models (Wilson 2010). All these research efforts expand PLS-SEM's applicability in marketing and management research.

While the recent methodological developments in PLS-SEM are radical, there are several promising avenues for further research. From a technical point of view, future research should aim at developing a global goodness-of-fit measure for PLS-SEM. This kind of model evaluation criterion is a key requirement for testing and comparing alternative theories with their associated models. Future research should also aim at providing corrections for the PLS-SEM bias regarding estimated relationships in the model. Based on its recent as well as promised methodological advances, PLS-SEM continues to become an ever-more commanding multivariate analysis tool for marketing research, with improved general usefulness in various research settings. In particular, the method supports the theoretical development of standard path models for assessing the success drivers of certain target constructs with key relevance for marketing management (e.g., in specific industry and company settings). Such models can become a valuable tool to frequently estimate, assess, monitor, and benchmark the key drivers.

Finally, even though we believe that PLS-SEM path modeling can indeed be a "silver bullet" if correctly applied, it is important to stress that we do not argue against the statistically more demanding CB-SEM method. CB-SEM and PLS-SEM are complementary in that the nonparametric and variance-based PLS-SEM approach's advantages are the parametric and covariance-based SEM approach's disadvantages and vice versa (Fornell and Bookstein 1982; Henseler, Ringle, and Sinkovics 2009; Jöreskog and Wold 1982; Lohmöller 1989; Schneeweiß 1991). Thus, the one method is not superior to the other in general—these kinds of statements are usually biased by researchers' methodological background and discipline. Depending on the specific empirical context and objectives of an SEM study, PLS-SEM's distinctive methodological features make it a valuable and potentially better-suited alternative to the more popular CB-SEM approaches.

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