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Special Issue

European Management Research Using Partial Least Squares Structural Equation Modeling (PLS-SEM)

Editorial

Hair, Sarstedt, Pieper, and Ringle's (2012) review study shows that partial least squares structural equation modeling (PLS-SEM) has become an increasingly applied multivariate analysis technique in management research. More recently, Richter, Sinkovics, Ringle, and Schlägel (2016) echo this result by showing that the number of PLS-SEM applications in (international) business research has increased substantially in the past few years. However, PLS-SEM is still new to many researchers who want to know: What exactly is PLS-SEM?

Most explanations limit themselves to the algorithm's statistical elucidations (e.g., Rigdon, 2013; Tenenhaus, Esposito Vinzi, Chatelin, & Lauro, 2005; H. O. A. Wold, 1982), while a few others include additional descriptions, such as PLS-SEM's historical background (e.g., Chin, 1998; Dijkstra, 2010, 2014; Lohmöller, 1989; Rigdon, 2012, 2014). Herman O.A. H. O. A. Wold (2006), the originator of the method, characterizes PLS-SEM as an "epoch-making 1960s innovation" that combines econometric prediction with the psychometric modeling of latent variables (also referred to as constructs), which multiple indicators (also referred to as manifest variables) determine. To provide a better understanding of the approach, Figure 1 shows a simple PLS path model with four latent variables, Y_1 to Y_4 (represented by circles), determined as the weighted sum of their assigned indicators x (represented by the rectangles). In other words, in the measurement model (also called the outer model), a block of directly observable indicators represents each latent variable that is not directly observable. In the structural model (also called the inner model), the latent variables have pre-defined and theoretically/conceptually established relationships. The goal of the PLS-SEM approach is to generate latent variable scores that jointly minimize the residuals of the ordinary least squares (OLS) regressions in the model (i.e., maximize the explanation). The resulting latent variable scores are unique and determine the case values of each observation. They also make it possible to predict the indicators (x_7-x_{12}) of the endogenous or dependent latent variables in the structural model (Y_3 and Y_4). In short, PLS-SEM is a variance-based method that estimates composites representing latent variables in path models. Hair, Hult, Ringle, and Sarstedt (2017), for example, provide additional explications of PLS-SEM, including details on how to create and estimate PLS path models and how to evaluate the results (also see Chin, 1998, 2010; Falk & Miller, 1992; Haenlein & Kaplan, 2004; Hair, Ringle, & Sarstedt, 2011; Henseler, Hubona, & Ray, 2016; Roldán & Sánchez-Franco, 2012; Tenenhaus, et al., 2005).

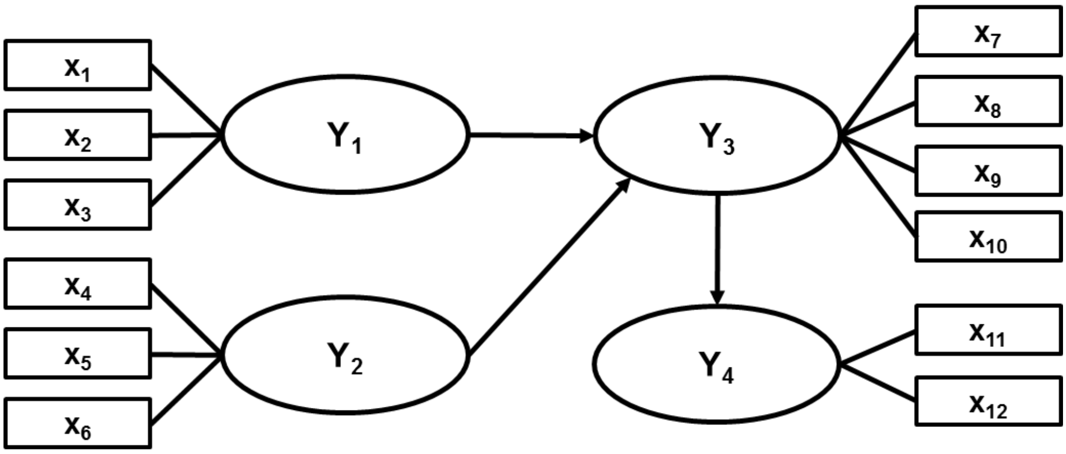


Figure 1: A Simple Path Model

An alternative perspective on the PLS-SEM method sees the exogenous or independent latent variables' indicators (i.e., x_1–x_6 on the left side of Figure 1) as the data input layer and the endogenous or dependent latent variables' indicators (i.e., x_7-x_{12} on the right side of Figure 1) as the data output layer. The latent variables and their relationships represent the structural model that connects the input and the output layer. While the input and output data change (e.g., across time, industries, companies, products, customers, and countries), the structural model and its latent variables represent the stable, theoretically/conceptually established connection between the observed data on the input and output sides. Based on the structural model, the goal of the analysis is to precisely predict the output layer data by means of the input layer data. To this end, the variance-based PLS-SEM approach uses OLS regressions and a structural model with latent variables, as well as the latter's relationships between the input and the output layers. "Thanks to the explicit case values of latent variables and structural residuals, the predictive relevance of a soft model can be explored by Stone-Geisser's cross-validation test" (H. O. A. Wold, 1982, p. 53). Against this background, it is possible to position PLS-SEM between covariance-based SEM (CB-SEM) and machine learning. While the former only focuses on the relationships between theory testing and confirmatory/explanatory modeling, the latter focuses primarily on prediction. If the two approaches are two ends of a continuum, PLS-SEM—with its prediction-oriented goal and its theoretically/conceptually established structural model of latent variables and their relationships—is, as shown in Figure 2, positioned between the two ends.

"Why should there be a difference between explaining and predicting? The answer lies in the fact that measurable data are not accurate representations of their underlying constructs. The operationalization of theories and constructs into statistical models and measurable data creates a disparity between the ability to explain phenomena at the conceptual level and the ability to generate predictions at the measurable level." (Shmueli, 2010, p. 293). Depending on the goal of the research, which guides the way the method is applied, PLS-SEM may be positioned closer to the one or the other pole. For example, if the aim is mainly the variance explanation of dependent variables and prediction, emphasis should be put on the evaluation of the model's OLS regression results and its predictive capabilities using corresponding evaluation criteria (Hair, et al., 2017; Shmueli, Ray, Velasquez Estrada, & Chatla, 2016). On the contrary, if the analysis focuses on confirmatory/explanatory modeling, researchers should consider newly proposed goodness-of-fit criteria (Dijkstra & Henseler, 2015a; Henseler, et al., 2014). The goal of study usually does not purely follow the one or the other pole of the characterized continuum but takes a position in between. Hence, researchers may consider both sets of evaluation criteria to different degrees. However, accomplishing highly satisfactory results in both directions can be difficult since “the ‘wrong’ model can sometimes predict better than the correct one” (Shmueli, 2010, p. 293).

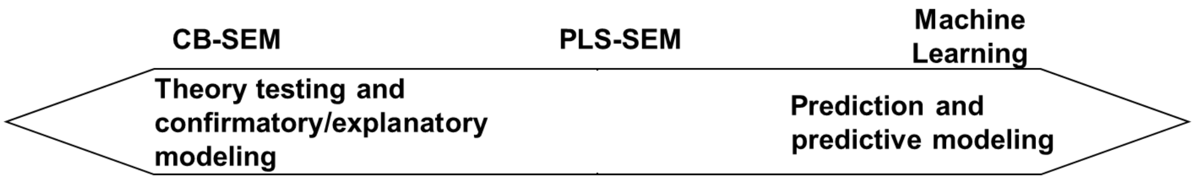


Figure 2: PLS-SEM as Method for Confirmatory/Explanatory and Predictive Modeling

The question that arises is the following: Why and when should PLS-SEM be used? H. O. A. Wold (2006) provides, among others, the following key reasons for using PLS-SEM: (a) the PLS-SEM approach has a broad scope and flexibility of theory and practice; and (b) a PLS path model develops through a dialogue between the investigator and the computer, in that tentative model improvements—such as the introduction of a new latent variable, an indicator, and an inner model relation, or the omission of such an element—are easily and quickly tested for predictive relevance. Moreover, prediction-oriented analyses, complex models, and secondary/archival or big data motivate the use of PLS-SEM (Gefen, Rigdon, & Straub, 2011; Rigdon, 2012, 2014). Additional reasons, suggested by Sarstedt, Ringle, and Hair (2016) and Rigdon (2016), are the use of composites that represent formatively measured latent variables, the use of small sample sizes due to a small population, applying PLS-SEM latent variable scores in subsequent analyses, and endeavoring to overcome factor-based SEM’s limitation by mimicking the results of common factor models (i.e., by using consistent PLS approaches; Bentler & Huang, 2014; Dijkstra & Henseler, 2015a).

H. O. A. Wold (2006) notes that in large and complex models with latent variables, PLS-SEM is “virtually without competition.” It has not only drastically reduced the distance between subject matter analysis and statistical technique but also reinvented the modeling of complex systems in domains with access to a steady flow of reliable data. In this context, H. O. A. Wold (1982), and later Chin (1998), expected PLS-SEM to be widely used across disciplines with rich data, such as classical (political) economics, education, health care and medicine, political science, and chemistry. However, management and other social sciences have traditionally had limited access to rich data because surveys that are subject to several restrictions (e.g., the number of questions) have usually provided most of the relevant data. With the ever-increasing availability of secondary data (e.g., from company databases, social media, and customer tracking), this situation has started to change dramatically. In fact, secondary and/or big data and PLS-SEM’s soft modeling approach fit hand in glove: “Soft modeling is primarily designed for research contexts that are simultaneously data-rich and theory-skeletal.” (H. O. A. Wold, 1982, p. 29); also see Rigdon (2013).

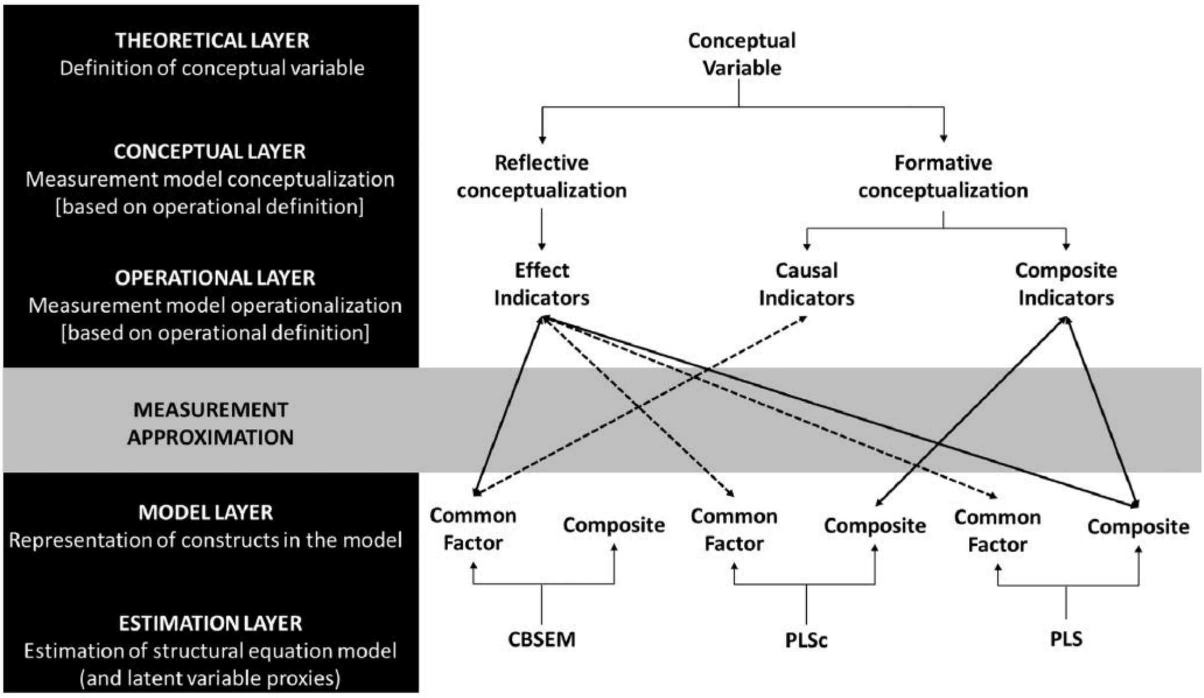
During the past decade, authors, reviewers, and editors have fully accepted PLS-SEM as a multivariate analysis method. A Google Scholar search on the term “partial least squares path modeling” reveals that it has helped thousands of researchers to empirically substantiate their theoretical project developments. The results of various review studies and overview articles across different disciplines, including accounting (L. Lee, Petter, Fayard, & Robinson, 2011; Nitzl, 2016), family business (Sarstedt, Ringle, Smith, Reams, & Hair, 2014), management information systems (Hair, Hollingsworth, Randolph, & Chong, 2016; Ringle, Sarstedt, & Straub, 2012), (international) marketing (Hair, Sarstedt, Ringle, & Mena, 2012; Henseler, Ringle, & Sinkovics, 2009; Richter, et al., 2016), operations management (Peng & Lai, 2012), supply chain management (Kaufmann & Gaeckler, 2015), strategic management (Hair, Sarstedt, Pieper, et al., 2012), and tourism (do Valle & Assaker, 2016) supports this notion further. While PLS-SEM applications have been published in a wide range of different research disciplines, including their top journals, some articles are even the most cited ones published in these journals (e.g., Hair, et al., 2011; Henseler, et al., 2009). A particularly prominent example is the article by Hair, Sarstedt, Ringle, et al. (2012), which, in the first five years after its publication, has become the most cited marketing article (Shugan, 2016). A Google Scholar search also reveals that the use of PLS-SEM has recently expanded into other research areas such as biology, medicine, engineering, political science, and psychology.

Various improvements, extensions, and methodological advances contribute to the method's popularity. The methodological toolbox is continually becoming richer, which leads to researchers accepting it as a useful method for their applications to an ever-greater degree. Noteworthy PLS-SEM advances address:

- the model estimation by means of covariance-based PLS algorithms (Lohmöller, 1989) and consistent PLS algorithms (Bentler & Huang, 2014; Dijkstra, 2014; Dijkstra & Henseler, 2015b) and through approaches to non-recursive models (Dijkstra & Henseler, 2015a), second-order models (Becker, Klein, & Wetzels, 2012; Caviolino & Nitti, 2013; Ringle, et al., 2012; Wright, Campbell, Thatcher, & Roberts, 2012), mediator models (Nitzl, Roldán, & Cepeda Carrión, 2016), non-linear models (Rigdon, Ringle, & Sarstedt, 2010), and a better understanding of single-item constructs (Diamantopoulos, Sarstedt, Fuchs, Wilczynski, & Kaiser, 2012; Sarstedt, Diamantopoulos, & Salzberger, 2016; Sarstedt, Diamantopoulos, Salzberger, & Baumgartner, 2016);
- results evaluation by means of confirmatory tetrad analysis to test the kind of measurement model (CTA-PLS; Gudergan, Ringle, Wende, & Will, 2008), common method variance analysis (Chin, Thatcher, & Wright, 2012; Chin, Thatcher, Wright, & Steel, 2013), the heterotrait–monotrait ratio of correlations (HTMT) in order to assess discriminant validity (Henseler, Ringle, & Sarstedt, 2015), the overall goodness-of-fit measures (Dijkstra & Henseler, 2015a; Henseler, et al., 2014), and methods for uncovering unobserved heterogeneity (e.g., Becker, Rai, Ringle, & Völckner, 2013; Hahn, Johnson, Herrmann, & Huber, 2002; Ringle, Sarstedt, & Schlittgen, 2014; Ringle, Sarstedt, Schlittgen, & Taylor, 2013; Sarstedt, Becker, Ringle, & Schwaiger, 2011);
- and complementary techniques, such as the moderator analysis (Henseler & Chin, 2010; Henseler & Fassott, 2010), multigroup analysis approaches (e.g., Chin & Dibbern, 2010; Sarstedt, Henseler, & Ringle, 2011), the measurement invariance test of composites (Henseler, Ringle, & Sarstedt, 2016), and the importance-performance map analysis (Ringle & Sarstedt, 2016).

All these advances have led to new insights and guidelines on how to use PLS-SEM (Hair, et al., 2017; Henseler, Hubona, et al., 2016), updated primers on PLS-SEM (Hair, et al., 2017), and new textbooks on PLS-SEM advances (Hair, Sarstedt, Ringle, & Gudergan, 2018) that the researcher can refer to.

Parallel and owing to these developments, researchers have recently called for the emancipation of PLS-SEM from CB-SEM, to which the method is routinely compared (e.g., Rigdon, 2012, 2014; Sarstedt, Ringle, Henseler, & Hair, 2014). These authors maintain that "PLS path modeling can and should separate itself from factor-based SEM and renounce entirely all mechanisms, frameworks and jargon associated with factor models." (Rigdon, 2012, p. 353). Using common factor model-based SEM as a point of reference and using PLS-SEM to mimic the results led to a lot of confusion, criticism, and ambiguity regarding the terminology used. Recently, Henseler, Ringle, et al. (2016) proposed a framework that solves this problem and supports PLS-SEM's emancipation. This framework (Figure 3) distinguishes the theoretical, conceptual, and operational layer from the statistical model layer and the estimation layer. In line with Rigdon (2012, 2014), this framework postulates that statistical methods only approximate conceptual variables in theoretical models by means of constructs in statistical models: "Whereas the theoretical layer serves to define the conceptual variable, the conceptual layer delivers the operational definition of the conceptual variables, which then serves as the basis for the measurement operationalization using effect, causal, or composite indicators on the operational layer. This conceptualization and operationalization of construct measures represents the measurement perspective. This perspective needs to be complemented with the model estimation perspective. The estimation layer intertwines with the measurement model layer that expresses how the data represent reflectively or formatively specified measurement models." (Sarstedt, Hair, Ringle, Thiele, & Gudergan, 2016). These authors also show that PLS-SEM is optimal for estimating composite models while it simultaneously allows the approximation of common factor models involving effect indicators (Figure 3).



Notes: Dashed lines indicate acceptable types of measurement approximation; solid lines represent recommended types of measurement approximation. The PLSc results when estimating composite model data and composite indicators parallel those from PLS as no correction for attenuation occurs.

Figure 3: Measurement and Model Estimation Framework (Henseler, Ringle, et al., 2016)

Another core PLS-SEM emancipation element builds on the aforementioned idea of prediction and predictive modeling. "Insights from the forecasting literature suggest that PLS path modeling has strengths as a tool for prediction which have not been fully appreciated" (Rigdon, 2012, p. 341). The Stone–Geisser test (Geisser, 1974; Stone, 1974) permits a prediction-oriented evaluation of PLS-SEM results (H. O. A. Wold, 1982). Although highly necessary, additional result evaluations and advances that emphasize PLS-SEM's prediction-oriented use are very rare or in an early stage of development. Recently, the *Journal of Business Research* special issue on PLS-SEM and prediction (Cepeda Carrión, Henseler, Ringle, & Roldán, 2016) addressed this issue by showing the predictive estimation capabilities of PLS-SEM (Evermann & Tate, 2016) and how segmentation can improve the prediction (Schlittgen, Ringle, Sarstedt, & Becker, 2016), suggesting a new prediction-oriented evaluation procedure (Shmueli, et al., 2016) and extending PLS-SEM results' predictive range in combination with the agent-based simulation method (Schubring, Lorscheid, Meyer, & Ringle, 2016). However, future PLS-SEM research still offers many opportunities for methodological extensions. The call to establish predictive modeling in the social sciences disciplines could be a key point of orientation and reference for such research (Shmueli, 2010; Shmueli & Koppius, 2010). As shown in Figure 4, a predictive modeling process must define all of its modeling process steps, just as confirmatory/explanatory modeling does. This process is an ideal point of orientation for future research on predictive modeling and PLS-SEM use, and the topics need to be systematically addressed.

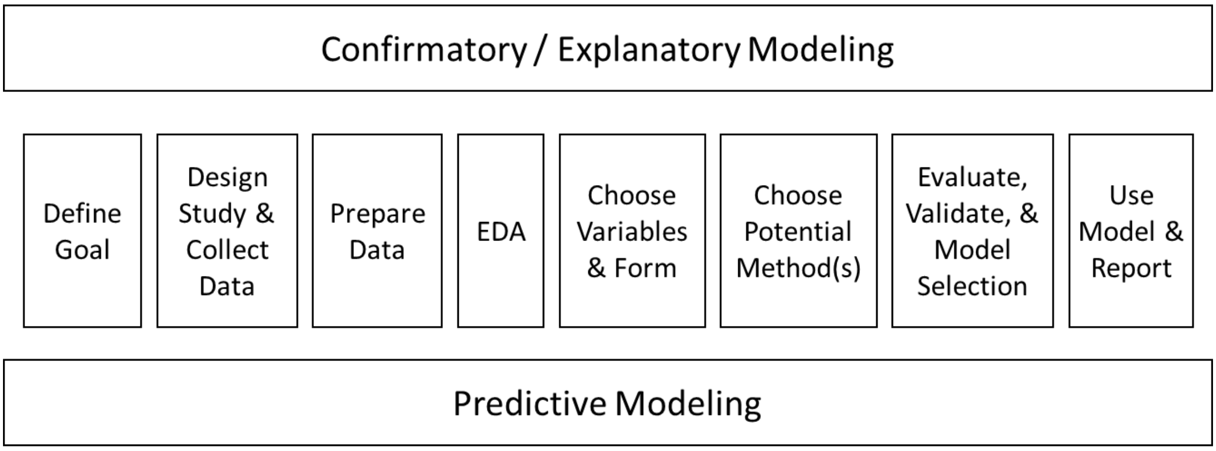


Figure 4: The Modeling Process (Adapted From Shmueli, 2010)

Other extensions of the method, which management researchers in particular require, include the estimation of PLS path models with longitudinal data or panel data (Bookstein, Sampson, Streissguth, & Barr, 1996; Henning-Thurau, Groth, Paul, & Gremler, 2006; Johnson, Herrmann, & Huber, 2006; D. Y. Lee, 1997; Roxas, 2013; Shea & Howell, 2000) and how the results should be assessed. In addition, management researchers call for combining the multilevel model analysis (Goldstein, 2011; Hox, Moerbeek, & van de Schoot, 2010; Snijders & Bosker, 2012) with PLS-SEM in a newly developed multilevel PLS-SEM technique. Finally, in the case of using PLS-SEM for confirmatory/explanatory purposes, management research needs to address the issue of endogeneity by using suitable control or instrumental variables and other techniques (Benitez, Henseler, & Roldán, 2016; Ebbes, Papies, & van Heerde, 2011; Semadeni, Withers, & Trevis Certo, 2014); for prediction-oriented research, endogeneity is not an issue, and researchers can draw directly on PLS-SEM's estimation results, which draw on OLS regressions. For the predictive PLS-SEM analysis purposes, however, future research should aim at exploiting the capabilities of the PLS regression method (Höskuldsson, 1988; Tenenhaus & Esposito Vinzi, 2005; S. Wold, Sjöström, & Eriksson, 2001) and the deflation technique (Esposito Vinzi, Trinchera, & Amato, 2010; Löfstedt, Hanafi, & Trygg, 2013; Lohmöller, 1989).

While much has been accomplished, the emancipation of PLS-SEM is still in its early stages. Many small steps and advances are still needed before the chains to emancipation are broken (Rigdon, 2014). With the continuing dissemination of PLS-SEM to management and other disciplines, this special issue is another important cornerstone in PLS-SEM use's orientation. It introduces advanced methods that support researchers, and it shows the empirical application of PLS-SEM to research problems in management. Our call for papers in the "*European Management Journal* Special Issue on European Management Research Using Partial Least Squares Structural Equation Modeling (PLS-SEM)" (Richter, Cepeda, Roldán, & Ringle, 2015) led to 66 manuscripts being submitted. After a thorough review process, we finally accepted nine manuscripts that comprise this special issue. The first four manuscripts contribute to the advanced use of the PLS-SEM method, while the latter five present PLS-SEM applications in management. In the following, we briefly introduce each paper.

There is currently heightened controversy over the value of PLS-SEM as a quantitative research method, including the domain of European management research. On the one hand, critical lines of argument within the management and psychology literature assert that there is no reason to use PLS-SEM at all. In this vein, there are critics who offer flawed reasons to avoid PLS-SEM. Some of these critical arguments falsely ascribe advantageous properties to the factor-based approach to SEM that do not exist, while others are based on flawed evidence about the performance of PLS-SEM. On the other hand, authors using PLS-SEM continue to advance fallacious arguments to justify their choice of method, citing non-existent strengths or advantages for PLS-SEM. In this regard, the first paper of this special issue, *"Choosing PLS path modeling as analytical method in European management research: A realist perspective" (Rigdon, 2016),* aims to review and correct both types of errors, both alleged weaknesses and alleged strengths or advantages of PLS-SEM, which have not been supported by valid evidence. To this end, this article addresses this challenge within the context of a unifying framework and a realist philosophy of science and provides three major contributions. First, it will help researchers to make better design and method choices; second, it will guide writers to avoid crucial errors in explaining their choices; and finally, it will help to move the SEM dialogue forward.

Researchers seeking to draw conclusions about the behavior and relationships prevalent in populations of interest (e.g., to the management of European firms) need to ensure that their samples represent these populations sufficiently. Sampling designs do not always generate observations that will have the same probability of selection as their occurrence in the population. Therefore, a common practice is to apply sampling weights to the data collected to avoid a bias that may arise in the parameter estimates and consequently avoid misleading interpretations. In this regard, the second (method-related) paper, *"Accounting for sampling weights in PLS path modeling: Simulations and empirical examples" (Becker & Ismail, 2016)*, offers two contributions. First, it develops a new weighted partial least squares (WPLS) structural equation modeling algorithm that provides consistent population estimates using sampling weights in a PLS-SEM context. Second, it provides researchers with guidelines on how to generate sampling weights and how to alter the basic PLS-SEM algorithm to take these weights into account. The authors demonstrate that their procedure can correct imperfections in the sample, for example, those resulting from unequal probabilities of selection but also from unit non-response and non-coverage. For this reason, the authors conduct a simulation study and refer to an illustrative job attitude model using SmartPLS 3, which implements the suggested WPLS approach.

A third (method-related) paper concentrates on the correct use of bootstrapping. Obtaining statistical inference from bootstrapping procedures is one of the aims that researchers have when using PLS-SEM. *"Bootstrapping and PLS-SEM: A step-by-step guide to get more out of your bootstrap results" (Streukens & Leroi-Werelds, 2016)* presents how bootstrapping can help researchers to develop practically relevant studies and generate rigorous theory. A review of the application of PLS-SEM bootstrap procedures in the European management context reveals that there is much room for improvement regarding the optimal conduct and reporting of bootstrapping. This methodological paper shows how bootstrapping can help researchers in their PLS-SEM applications, and it outlines bootstrapping best practices to assess (non-)direct effects, effects comparison, and R^2 evaluation.

Finally, the paper *"Assessing the measurement invariance of the four-dimensional cultural intelligence scale across countries: A composite model approach" (Schlägel & Sarstedt, 2016)* makes two contributions: one content-related and one methodological contribution. In the management of European firms, the cultural intelligence of employees is a crucial determinant to establish and maintain good international business relationships within the firm and with external partners. To assess the cultural intelligence of their (potential) employees, as well as the relation to its determinants and outcomes, a four-dimensional scale that is common practice in research can be used. However, as with any scale to be used in cross-country or cross-cultural settings, researchers need to establish measurement invariance. In this regard, the authors, first, demonstrate the application of the recently proposed measurement invariance of composite model (MICOM) procedure and therewith offer guidelines for evaluating measurement invariance of scales across multiple countries in a PLS-SEM context. Second, the authors contribute to further advancing (the precision and meaningfulness of) the cultural intelligence scale. Their results indicate that certain dimensions of the construct are generalizable to other countries (i.e. etic) and might be used as a set of core items to be universally applied. Other items, however, are strongly culturally bound (or emic), i.e. cross-cultural differences in norms, values, and beliefs substantially alter their meaning. These items could be added to the scales depending on the specific cultural context. For the purposes above, the authors refer to a set of respondents across five countries (China, France, Germany, Turkey, and the US) and research into the effect on respondent's expatriation intentions.

Five other papers present PLS-SEM applications in the European management context from a strategy and marketing perspective. In recent years, massive firm failures have occurred, triggering economic shock and a global financial crisis. These failures, both ethical and strategic, have been at least in part a consequence of undue short-term focus on shareholder monetary returns versus the interests of other stakeholders. In addition, demands for corporate social responsibility, sustainability, and increasing regulatory requirements dictate that firms consider the needs of multiple stakeholders. Thus, the stakeholder theory suggests that firms should be sensitive to a broad group of stakeholders and their needs, with balanced trade-offs that are fundamental to achieving sustainable competitive advantage, and ultimately survival. On the other hand, market orientation (MO) scholars consistently call for the inclusion of a broader group of stakeholders than the widely studied customer and competitor groups in order to gain a better understanding of the impact of multiple stakeholders on firm performance. In this respect, the paper "*Is stakeholder orientation relevant for European firms?" (Patel, Manley, Hair, Ferrell, & Pieper, 2016)* offers two contributions. First, it expands the traditional domain of MO and defines overall stakeholder orientation as one that includes customers, competitors, employees, and shareholders, designating them as core and essential stakeholders. Second, since scholars have also advocated for the inclusion of more forward-looking, proactive considerations in the conceptual framework to complement the usual responsive aspects of MO, this study includes measures for both proactive and responsive orientations for the four core stakeholder groups representing overall stakeholder orientation. The results show that for European firms, proactive considerations are potentially more impactful than responsive, and overall stakeholder orientation is a significant predictor of improved financial and nonfinancial performance. For this purpose, the authors apply a PLS-SEM approach to a sample of firms from five European countries: Austria, France, Germany, Netherlands, and the UK. Furthermore, for the four core stakeholder groups, they develop and validate new measures for both proactive and responsive orientations.

The second application-related paper also takes a strategy perspective. It concentrates on knowledge management (KM) and total quality management (TQM). In the paper

"Excellence management practices, knowledge management and key business results in large organizations and SMEs: A multi-group analysis" (Calvo-Mora, Navarro-García, Rey-Moreno, & Periañez-Cristobal, 2016), the authors carry out intensive work to study the influence of process methodology and partner management on KM and organizational outcomes. The paper provides a PLS-SEM application to a very complex model in the European context: After analyzing the metric invariance of the composites that permits the permutations analysis, the authors carry out a multigroup analysis adopting a non-parametric test of permutations. The findings reveal that the use of process methodology and partners' commitment are critical factors for the impact of KM on organizational outcomes, both in SMEs and large firms. Furthermore, this study demonstrates that the impact of process methodology on KM is stronger in SMEs. In turn, the impact of partner involvement is higher for large firms. These findings are generated on a sample of 225 Spanish firms, and the authors use the original measures of the EFQM model to operationalize their variables.

Developing and sustaining successful cross-sector partnerships – be they equity and non-equity alliances or other forms of cooperation between partners in different sectors – is one of the major challenges to European managers. Managers need to develop an understanding of the many factors involved in forming (e.g. different values) and implementing (e.g. cooperation and learning) successful partnerships, and researchers need to provide the necessary insights into the intricacies of these factors. In this regard, the third application-related paper, *"Cross-sector social partnership success: A process perspective on the role of relational factors" (Barroso-Méndez, Galera Casquet, Seitanidi, & Valero-Amaro, 2016)*, provides a model of partnership success that links antecedent factors of partnership formation, namely shared values and the level of opportunistic behavior, to two types of relational factors relevant to the implementation phase. These are commitment and trust (i.e. preconditions of relational effects), as well as learning and cooperation (i.e. relational effects). The authors show that it is crucial to select partners that share a large set of common values and beliefs and to dedicate more time and effort to the development of trust and commitment during the partnership implementation. Moreover, they show that it is essential to maintain a high level of commitment while promoting the development of a culture of mutual learning within partnerships. To generate these results, the authors use a PLS-SEM approach on a sample of Spanish businesses. They implement various second-order constructs and develop a scale of partnership success using PLS.

Likewise related to partnership, in their paper "*Spirituality as an antecedent of trust and network commitment: The case of Anatolian Tigers", Kurt, Yamin, Sinkovics, and Sinkovics (2016)*, the authors explore the issue of spirituality on trust and network commitment in a specific context in Turkey. Their aim is to understand the role of spirituality, modeled as a second-order construct, for the commitment within a network of firms (i.e. Anatolian Tigers). This paper is a PLS-SEM application, and the authors find a partial mediation of trust in the relationship between spirituality and network commitment. Additionally, the authors consider the length of membership and firm size as control variables; however, the study proves the non-significance of both variables in the model proposed. Hence, it contributes to European management research and practice by analyzing spirituality as an antecedent to the commitment within a network. In order to test their hypotheses, the authors carry out a survey and obtain 120 valid questionnaires using face-to-face interviews.

Last but not least, there is one PLS-SEM application in the marketing context: At present, the analysis of customer loyalty continues to be an area of immense relevance and interest for both marketing scholars and practitioners. In particular, owing to the consequences of loyalty, managing to achieve customer loyalty is one of the principal objectives for service firms.

These consequences include a greater probability of completing new purchases, higher profits, withstanding the actions of rival firms, and lower retention costs. In this vein, the paper "*A mediating and multigroup analysis of customer loyalty*" *(Picón Berjoyo, Ruiz-Moreno, & Castro, 2016)* provides two main contributions. First, the authors propose a model for the generation of loyalty (both affective and behavioral) based on perceived value, through two mediator variables: customer satisfaction and perceived switching costs (PSCs). Second, the authors study the moderating effect of customer heterogeneity based on psychographic factors – in particular, the tendency toward loyalty – on the relationships that are established in their model. Their results show that perceived value has a direct influence on affective loyalty and an indirect influence through two mediating variables, while only PSCs play a mediating role in the case of behavioral loyalty. In addition, the tendency toward loyalty has a significant moderating impact on the relations between satisfaction and affective loyalty and the relation between PSCs and both affective and behavioral loyalty. Finally, the authors observe that the proposed model presents greater explanatory power for customers with a higher tendency toward loyalty. To generate these results, the authors use a PLS-SEM approach on a sample of 786 customers of Spanish insurance companies, applying mediation analysis, latent segmentation, and multigroup analysis.

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