European Management Journal xxx (2016) 1–9

Contents lists available at ScienceDirect

European Management Journal

journal homepage: www.elsevier.com/locate/emj

Editorial

European management research using partial least squares structural equation modeling (PLS-SEM)

Keywords:
Management research
Partial least squares (PLS)
Structural equation modeling (SEM)
Path modeling
Quantitative methods
Method development
Empirical application

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; 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. 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, Fig. 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 (i.e., the algorithm provides determinate latent variable scores). 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).

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 Fig. 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 Fig. 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 contextual link between the observed data on the input and output sides. Based on the structural model, the goal of the analysis is to 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" (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 Fig. 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

http://dx.doi.org/10.1016/j.emj.2016.08.001

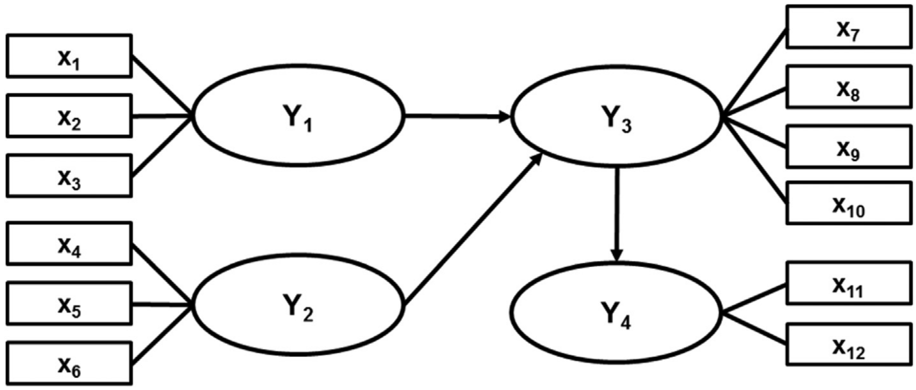

Fig. 1. A simple path model.

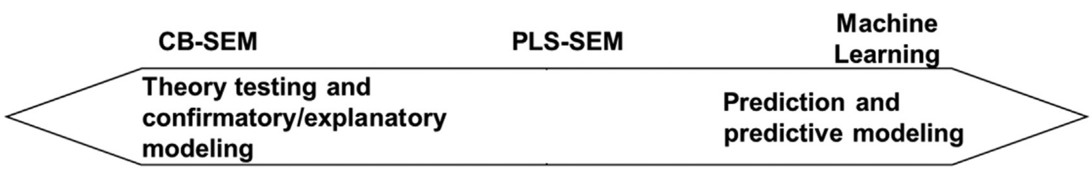

Fig. 2. PLS-SEM as method for confirmatory/explanatory and predictive modeling.

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 shown in Fig. 2. 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 the newly proposed consistent PLS approach (Bentler & Huang, 2014; Dijkstra & Henseler, 2015b; Dijkstra, 2014) and the use of PLS-SEM goodness-of-fit criteria (Dijkstra & Henseler, 2015a; Henseler et al., 2014). However, 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. But 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).

The question that arises is the following: Why and when should PLS-SEM be used? 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, 2015b).

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, 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." (Wold, 1982, p. 29; also see Rigdon, 2013).

During the past decade, authors, reviewers, and editors have widely 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/conceptual project developments. The results of various review studies and overview articles across different disciplines, including accounting (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,

Please cite this article in press as: Richter, N. F., et al.European management research using partial least squares structural equation modeling (PLS-SEM), European Management Journal (2016), http://dx.doi.org/10.1016/j.emj.2016.08.001

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 & Henseler, 2015b; Dijkstra, 2014) as well as 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, et al., 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; Voorhees, Brady, Calantone, & Ramirez, 2016), 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, &

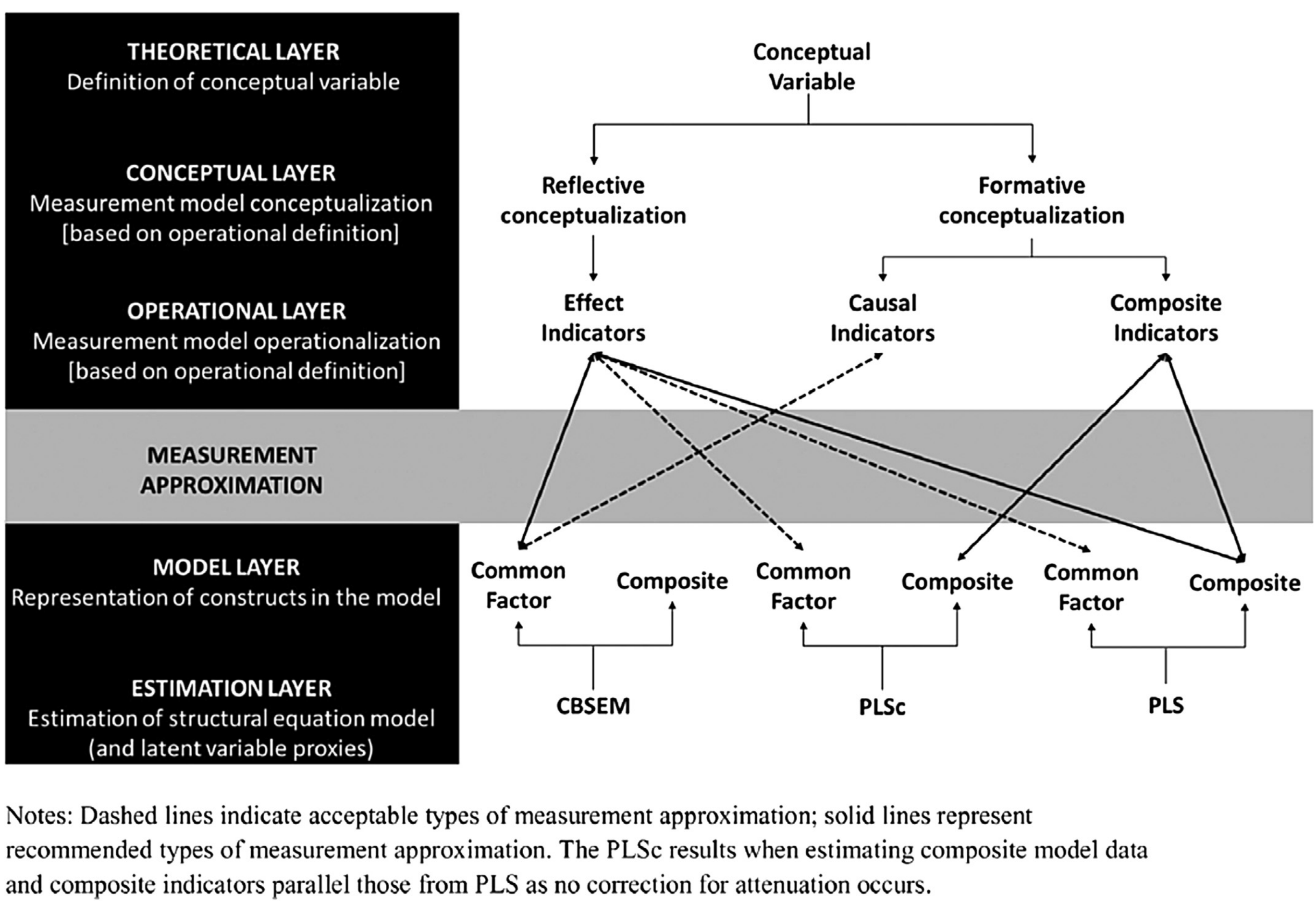

Fig. 3. Measurement and model estimation framework (Henseler, Ringle et al., 2016).

Please cite this article in press as: Richter, N. F., et al.European management research using partial least squares structural equation modeling (PLS-SEM), European Management Journal (2016), http://dx.doi.org/10.1016/j.emj.2016.08.001

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 (Fig. 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 ,p. 4006). 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 (Fig. 3).

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 (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 & Koppius, 2010; Shmueli, 2010). As shown in Fig. 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.

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; 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; Lohmöller, 1989; Löfstedt, Hanafi, & Trygg, 2013).

While much has been accomplished, the emancipation of PLS-SEM is still in its early stages. Many small steps and advances are

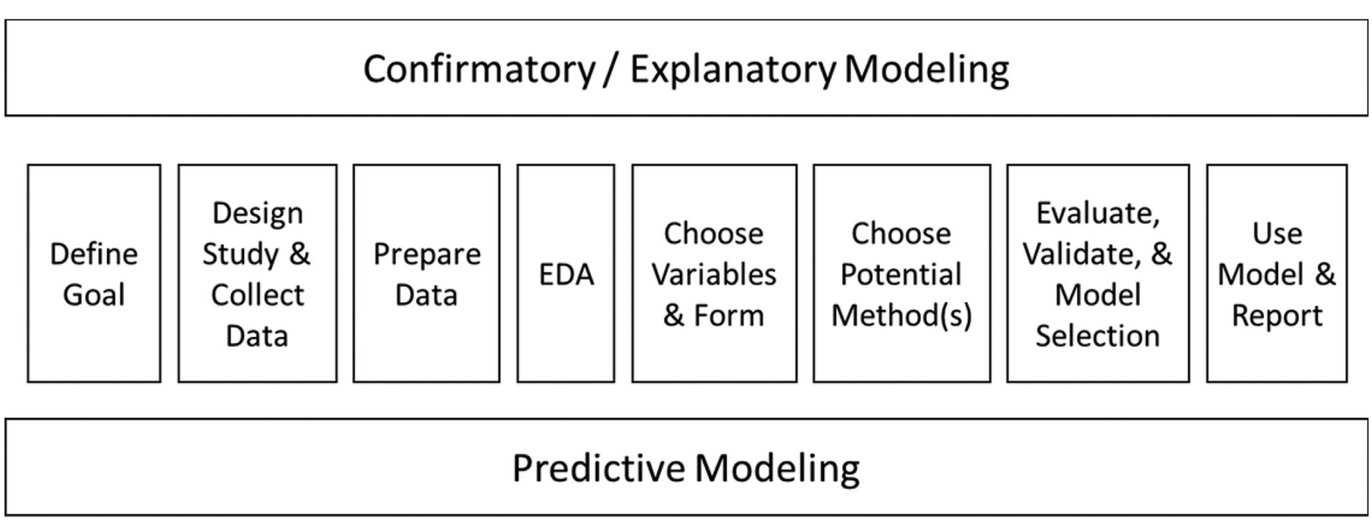

Fig. 4. The modeling process (Adapted from Shmueli, 2010).

Please cite this article in press as: Richter, N. F., et al.European management research using partial least squares structural equation modeling (PLS-SEM), European Management Journal (2016), http://dx.doi.org/10.1016/j.emj.2016.08.001

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 (Ringle, Wende, & Becker, 2015), 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. 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 European Foundation for Quality Management (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-SEM.

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) explore the role of spirituality for 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). They apply PLS-SEM and 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.

We are very grateful to the reviewers who contributed their valuable time and talent to develop this special issue and ensured the articles' quality through their constructive comments and suggestions to the authors. The reviewers for the *European Management Journal* special issue on PLS-SEM include: Hervé Abdi, Francisco J. Acedo-González, Dennis C. Ahrholdt, Julen Castillo-Apraiz, Daniel Arenas-Vives, Claudia Astrachan-Binz, Alina Baluch, Boris Bartikowski, Ralf Bebenroth, Jan-Michael Becker, Michael Bendixen, Antonio Juan Briones-Peñalver, Arturo Calvo de Mora-Schmidt, Jesús Cambra-Fierro, José Carlos Casillas-Bueno, Ignacio Castro-Abancens, Juan Gabriel Cegarra-Navarro, Amparo Cervera-Taulet, David Drabe, Andreas Eggert, Ángel F. Agudo-Peregrina, Keith E. Ferguson, Dave Garson, James Gaskin, Salomé Goñi-Legaz, Mª Rosario González-Rodríguez, Siegfried P. Gudergan, Marjaana Gunkel, Joseph F. Hair, Sven Hauff, Anne-Kathrin Hegner-Kakar, Jörg Henseler, Daniel Jiménez-Jiménez, Dean Lim, Iris Lorscheid, Catarina Antunes Marques, Silvia Martelo-Landroguez, Eva Martínez-Caro, Mehmet Mehmetoglu, David Midgley, Rebecca Mitchell, Dirk Morschett, Christian Nitzl, Shintaro Okazaki, Araceli Picón-Berjoyo, Torsten M. Pieper, Martin Puppatz, Mercedes Sánchez-Apellániz, Agustín J. Sánchez-Medina, María L. Santos-Vijande, Marko Sarstedt, Christopher Schlägel, Manfred Schwaiger, Christoph Stockstrom, Laura Trinchera, Robert van der Veen, Martin Wetzles, Ralf Wilden, and Hsin-Hung Wu. Thanks again for your support!

Finally, we would like to use this opportunity to thank Sabina

Please cite this article in press as: Richter, N. F., et al.European management research using partial least squares structural equation modeling (PLS-SEM), European Management Journal (2016), http://dx.doi.org/10.1016/j.emj.2016.08.001

Siebert (University of Glasgow), editor-in-chief of the *European Management Journal*, for giving us the opportunity to develop this special issue. We also extend our thanks to Joannah Duncan (University of Glasgow) for all her kind support and the solutions she provided during the special issue's development process. We experienced excellent support from the editor and the editorial office while preparing this special issue. We sincerely look forward to seeing you continue this outstanding work by further developing the *European Management Journal*!

The *European Management Journal* Special Issue guest editors

Nicole Franziska Richter, University of Southern Denmark, Denmark, http://www.sdu.dk/en/

Gabriel Cepeda, Universidad de Sevilla, Spain, http://www.us.es/acerca/directorio/ppdi/personal_6194.

José Luis Roldán, Universidad de Sevilla, Spain, http://personal.us.es/jlroldan/Sitio_web/Index.html.

Christian M. Ringle, Hamburg University of Technology (TUHH), Germany, http://www.tuhh.de/hrmo/team/prof-dr-c-m-ringle.html, *and* University of Newcastle, Australia.

Acknowledgements

Even though this research does not explicitly refer to the use of the statistical software SmartPLS 3 (Ringle et al., 2015), Ringle acknowledges a financial interest in SmartPLS (http://www.smartpls.com).

References

Barroso-Méndez, M. J., Galera Casquet, C., Seitanidi, M. M., & Valero-Amaro, V. (2016). Cross-sector social partnership success: A process perspective on the role of relational factors. *European Management Journal* (in this issue).

Becker, J.-M., & Ismail, I. R. (2016). Accounting for sampling weights in PLS path modeling: Simulations and empirical examples. *European Management Journal* (in this issue).

Becker, J.-M., Klein, K., & Wetzels, M. (2012). Hierarchical latent variable models in PLS-SEM: Guidelines for using reflective-formative type models. *Long Range Planning, 45*, 359–394.

Becker, J.-M., Rai, A., Ringle, C. M., & Völckner, F. (2013). Discovering unobserved heterogeneity in structural equation models to avert validity threats. *MIS Quarterly, 37*, 665–694.

Benitez, J., Henseler, J., & Roldán, J. L. (2016). How to address endogeneity in partial least squares path modeling. In *22nd Americas conference on information systems (ACIS)* (San Diego, CA).

Bentler, P. M., & Huang, W. (2014). On components, latent variables, PLS and simple methods: Reactions to Rigdon's rethinking of PLS. *Long Range Planning, 47*, 138–145.

Bookstein, F. L., Sampson, P. D., Streissguth, A. P., & Barr, H. M. (1996). Exploiting redundant measurement of dose and developmental outcome: New methods from the behavioral teratology of alcohol. *Developmental Psychology, 32*, 404–415.

Calvo-Mora, A., Navarro-García, A., Rey-Moreno, M., & Periañez-Cristobal, R. (2016). Excellence management practices, knowledge management and key business results in large organizations and SMEs: A multi-group analysis. *European Management Journal* (in this issue).

Caviolino, E., & Nitti, M. (2013). Using the hybrid two-step estimation approach for the identification of second-order latent variable models. *Journal of Applied Statistics, 40*, 508–526.

Cepeda Carrión, G., Henseler, J., Ringle, C. M., & Roldán, J. L. (2016). Prediction-oriented modeling in business research by means of PLS path modeling. *Journal of Business Research, 69*, 4545–4551.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–358). Mahwah: Erlbaum.

Chin, W. W. (2010). How to write up and report PLS analyses. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Springer handbooks of computational statistics series: Vol. II. Handbook of partial least squares: Concepts, methods and applications* (pp. 655–690). Heidelberg, Dordrecht, London, New York: Springer.

Chin, W. W., & Dibbern, J. (2010). A permutation based procedure for multi-group PLS analysis: Results of tests of differences on simulated data and a cross cultural analysis of the sourcing of information system services between Germany and the USA. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Springer handbooks of computational statistics series: Vol. II. Handbook of partial least squares: Concepts, methods and applications* (pp. 171–193). Heidelberg, Dordrecht, London, New York: Springer.

Chin, W. W., Thatcher, J. B., & Wright, R. T. (2012). Assessing common method bias: Problems with the ULMC technique. *MIS Quarterly, 36*, 1003–1019.

Chin, W. W., Thatcher, J. B., Wright, R. T., & Steel, D. (2013). Controlling for common method variance in PLS analysis: The measured latent marker variable approach. In H. Abdi, W. W. Chin, V. Esposito Vinzi, G. Russolillo, & L. Trinchera (Eds.), *New perspectives in partial least squares and related methods* (pp. 231–239). New York, NY: Springer New York.

Diamantopoulos, A., Sarstedt, M., Fuchs, C., Wilczynski, P., & Kaiser, S. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: A predictive validity perspective. *Journal of the Academy of Marketing Science, 40*, 434–449.

Dijkstra, T. K. (2010). Latent variables and indices: Herman Wold's basic design and partial least squares. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Springer handbooks of computational statistics series: Vol. II. Handbook of partial least squares: Concepts, methods and applications* (pp. 23–46). Heidelberg, Dordrecht, London, New York: Springer.

Dijkstra, T. K. (2014). PLS'Janus face – Response to professor Rigdon's 'rethinking partial least squares modeling: In praise of simple methods'. *Long Range Planning, 47*, 146–153.

Dijkstra, T. K., & Henseler, J. (2015). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis, 81*, 10–23.

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly, 39*, 297–316.

Ebbes, P., Papies, D., & van Heerde, H. J. (2011). The sense and non-sense of holdout sample validation in the presence of endogeneity. *Marketing Science, 30*, 1115–1122.

Esposito Vinzi, V., Trinchera, L., & Amato, S. (2010). PLS path modeling: From foundations to recent developments and open issues for model assessment and improvement. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Springer handbooks of computational statistics series: Vol. II. Handbook of partial least squares: Concepts, methods and applications* (pp. 47–82). Heidelberg, Dordrecht, London, New York: Springer.

Evermann, J., & Tate, M. (2016). Assessing the predictive performance of structural equation model estimators. *Journal of Business Research* (in press).

Falk, R. F., & Miller, N. B. (1992). *A primer for soft modeling*. Akron, OH: University of Akron Press.

Gefen, D., Rigdon, E. E., & Straub, D. (2011). An update and extension to SEM guidelines for administrative and social science research. *MIS Quarterly, 35*, iii–xiv.

Geisser, S. (1974). A predictive approach to the random effects model. *Biometrika, 61*, 101–107.

Goldstein, H. (2011). *Multilevel statistical models* (fourth ed.). New York, NY: Wiley.

Gudergan, S. P., Ringle, C. M., Wende, S., & Will, A. (2008). Confirmatory tetrad analysis in PLS path modeling. *Journal of Business Research, 61*, 1238–1249.

Haenlein, M., & Kaplan, A. M. (2004). A Beginner's guide to partial least squares analysis. *Understanding Statistics, 3*, 283–297.

Hahn, C., Johnson, M. D., Herrmann, A., & Huber, F. (2002). Capturing customer heterogeneity using a finite mixture PLS approach. *Schmalenbach Business Review, 54*, 243–269.

Hair, J. F., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2016). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems* (in press).

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M.. (2017). A primer on partial least squares structural equation modeling (PLS-SEM) (second ed.). Thousand Oaks, CA: Sage.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice, 19*, 139–151.

Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012). The use of partial least squares structural equation modeling in strategic management research: A review of past practices and recommendations for future applications. *Long Range Planning, 45*, 320–340.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P.. (2018). Advanced issues in partial least squares structural equation modeling (PLS-SEM). Thousand Oaks, CA: Sage.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science, 40*, 414–433.

Henning-Thurau, T., Groth, M., Paul, M., & Gremler, D. D. (2006). Are all smiles created equal? How emotional contagion and emotional labor affect service relationships. *Journal of Marketing Theory and Practice, 70*, 58–73.

Henseler, J., & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural Equation Modeling, 17*, 82–109.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., et al. (2014). Common beliefs and reality about partial least squares: Comments on Rönkkö & Evermann (2013). *Organizational Research Methods, 17*, 182–209.

Henseler, J., & Fassott, G. (2010). Testing moderating effects in PLS path models: An illustration of available procedures. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Springer handbooks of computational statistics series: Vol. II. Handbook of partial least squares: Concepts, methods and applications* (pp. 713–735). Heidelberg, Dordrecht, London, New York: Springer.

Henseler, J., Hubona, G. S., & Ray, P. A. (2016). Using PLS path modeling in new

technology research: Updated guidelines. *Industrial Management & Data Systems, 116*, 1–19.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*, 115–135.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review, 33*, 405–431.
Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In R. R. Sinkovics, & P. N. Ghauri (Eds.), *Vol. 20. Advances in international marketing* (pp. 277–320). Bingley: Emerald.
Höskuldsson, A. (1988). PLS regression methods. *Journal of Chemometrics, 2*, 211–228.
Hox, J. J., Moerbeek, M., & van de Schoot, R. (2010). *Multilevel analysis: Techniques and applications* (second ed.). New York, NY: Routledge.
Johnson, M. D., Herrmann, A., & Huber, F. (2006). The evolution of loyalty intentions. *Journal of Marketing, 70*, 122–132.
Kaufmann, L., & Gaeckler, J. (2015). A structured review of partial least squares in supply chain management research. *Journal of Purchasing and Supply Management, 21*, 259–272.
Kurt, Y., Yamin, M., Sinkovics, N., & Sinkovics, R. R. (2016). Spirituality as an antecedent of trust and network commitment: The case of Anatolian Tigers. *European Management Journal* (in this issue).
Lee, D. Y. (1997). The impact of poor performance on risk-taking attitudes: A longitudinal study with a PLS causal modeling approach. *Decision Science, 28*, 59–80.
Lee, L., Petter, S., Fayard, D., & Robinson, S. (2011). On the use of partial least squares path modeling in accounting research. *International Journal of Accounting Information Systems, 12*, 305–328.
Löfstedt, T., Hanafi, M., & Trygg, J. (2013). Multiblock and path modeling with OnPLS. In H. Abdi, W. W. Chin, V. Esposito Vinzi, G. Russolillo, & L. Trinchera (Eds.), *New perspectives in partial least squares and related methods* (pp. 209–220). New York, NY: Springer New York.
Lohmöller, J.-B. (1989). *Latent variable path modeling with partial least squares*. Heidelberg: Physica.
Nitzl, C. (2016). The use of partial least squares structural equation modelling (PLS-SEM) in management accounting research: Directions for future theory development. *Journal of Accounting Literature* (in press).
Nitzl, C., Roldán, J. L., & Cepeda Carrión, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems* (in press).
Patel, V. K., Manley, S. C., Hair, J. F., Ferrell, O. C., & Pieper, T. M. (2016). Is stakeholder orientation relevant for European firms? *European Management Journal* (in this issue).
Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. *Journal of Operations Management, 30*, 467–480.
Picón Berjoyo, A., Ruiz-Moreno, C., & Castro, I. (2016). A mediating and multigroup analysis of customer loyalty. *European Management Journal* (in this issue).
Richter, N. F., Cepeda, G., Roldán, J. L., & Ringle, C. M. (2015). European management research using partial least squares structural equation modeling (PLS-SEM). *European Management Journal, 33*, 1–3.
Richter, N. F., Sinkovics, R. R., Ringle, C. M., & Schlägel, C. (2016). A critical look at the use of SEM in international business research. *International Marketing Review, 33*, 376–404.
Rigdon, E. E. (2016). Choosing PLS path modeling as analytical method in European management research: A realist perspective. *European Management Journal* (in this issue).
Rigdon, E. E. (2012). Rethinking partial least squares path modeling: In praise of simple methods. *Long Range Planning, 45*, 341–358.
Rigdon, E. E. (2013). Partial least squares path modeling. In G. R. Hancock, & R. O. Mueller (Eds.), *Structural equation modeling. A second course* (second ed., pp. 81–116). Charlotte NC: Information Age Publishing.
Rigdon, E. E. (2014). Rethinking partial least squares path modeling: Breaking chains and forging ahead. *Long Range Planning, 47*, 161–167.
Rigdon, E. E., Ringle, C. M., & Sarstedt, M. (2010). Structural modeling of heterogeneous data with partial least squares. In N. K. Malhotra (Ed.), *Vol. 7. Review of marketing research* (pp. 255–296). Armonk: Sharpe.
Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial Management & Data Systems, 116* (in press).
Ringle, C. M., Sarstedt, M., & Schlittgen, R. (2014). Genetic algorithm segmentation in partial least squares structural equation modeling. *OR Spectrum, 36*, 251–276.
Ringle, C. M., Sarstedt, M., Schlittgen, R., & Taylor, C. R. (2013). PLS path modeling and evolutionary segmentation. *Journal of Business Research, 66*, 1318–1324.
Ringle, C. M., Sarstedt, M., & Straub, D. W. (2012). A critical look at the use of PLS-SEM in MIS Quarterly. *MIS Quarterly, 36*, iii–xiv.
Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3*. Bönningstedt: SmartPLS GmbH.
Roldán, J. L., & Sánchez-Franco, M. J. (2012). Variance-based structural equation modeling: Guidelines for using partial least squares in information systems research. In M. Mora, O. Gelman, A. L. Steenkamp, & M. Raisinghani (Eds.), *Research methodologies, innovations and philosophies in software systems engineering and information systems* (pp. 193–221). Hershey, PA: IGI Global.
Roxas, B. (2013). Effects of entrepreneurial knowledge on entrepreneurial intentions: A longitudinal study of selected South-East Asian business students. *Journal of Education and Work, 27*, 432–453.
Sarstedt, M., Becker, J.-M., Ringle, C. M., & Schwaiger, M. (2011). Uncovering and Treating unobserved heterogeneity with FIMIX-PLS: Which model selection criterion provides an appropriate number of segments? *Schmalenbach Business Review, 63*, 34–62.
Sarstedt, M., Diamantopoulos, A., & Salzberger, T. (2016). Should we use single items? Better not. *Journal of Business Research, 69*, 3199–3203.
Sarstedt, M., Diamantopoulos, A., Salzberger, T., & Baumgartner, P. (2016). Selecting single items to measure doubly-concrete constructs: A cautionary tale. *Journal of Business Research, 69*, 3159–3167.
Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies! *Journal of Business Research, 69*, 3998–4010.
Sarstedt, M., Henseler, J., & Ringle, C. M. (2011). Multi-group analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results. In M. Sarstedt, M. Schwaiger, & C. R. Taylor (Eds.), *Vol. 22. Advances in international marketing* (pp. 195–218). Bingley: Emerald.
Sarstedt, M., Ringle, C. M., & Hair, J. F. (2016). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of market research*. Heidlebert: Springer (in press)
Sarstedt, M., Ringle, C. M., Henseler, J., & Hair, J. F. (2014). On the emancipation of PLS-SEM: A commentary on Rigdon (2012). *Long Range Planning, 47*, 154–160.
Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy, 5*, 105–115.
Schlägel, C., & Sarstedt, M. (2016). Assessing the measurement invariance of the four-dimensional cultural intelligence scale across countries: A composite model approach. *European Management Journal* (in this issue).
Schlittgen, R., Ringle, C. M., Sarstedt, M., & Becker, J.-M. (2016). Segmentation of PLS path models by iterative reweighted regressions. *Journal of Business Research, 69*, 4583–4592.
Schubring, S., Lorscheid, I., Meyer, M., & Ringle, C. M. (2016). The PLS agent: Predictive modeling with PLS-SEM and agent-based simulation. *Journal of Business Research, 69*, 4604–4612.
Semadeni, M., Withers, M. C., & Trevis Certo, S. (2014). The perils of endogeneity and instrumental variables in strategy research: Understanding through simulations. *Strategic Management Journal, 35*, 1070–1079.
Shea, C. M., & Howell, J. M. (2000). Efficacy-performance spirals: An empirical test. *Journal of Management, 26*, 791–812.
Shmueli, G. (2010). To explain or to predict? *Statistical Science, 25*, 289–310.
Shmueli, G., & Koppius, O. R. (2010). Predictive analytics in information systems research. *MIS Quarterly, 35*, 553–572.
Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Evaluating the predictive performance of PLS models. *Journal of Business Research* (in press).
Shugan, S. M. (2016). *Shugan's top 20 marketing meta-journal (most cited marketing Articles): Top 20 articles published after 5/1/2012 (cites as of 5/31/2016)* (Vol. 3). Universtiy of Florida. Issue 5 May. http://bear.warrington.ufl.edu/centers/mks/vol3no05.htm.
Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling* (second ed.). Thousand Oaks, CA: Sage.
Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society, 36*, 111–147.
Streukens, S., & Leroi-Werelds, S. (2016). Bootstrapping and PLS-SEM: A step-by-step guide to get more out of your bootstrap results. *European Management Journal* (in this issue).
Tenenhaus, M., & Esposito Vinzi, V. (2005). PLS regression, PLS path modeling and generalized procrustean analysis: A combined approach for multiblock analysis. *Journal of Chemometrics, 19*, 145–153.
Tenenhaus, M., Esposito Vinzi, V., Chatelin, Y.-M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis, 48*, 159–205.
do Valle, P. O., & Assaker, G. (2016). Using partial least squares structural equation modeling in tourism research: A review of past research and recommendations for future applications. *Journal of Travel Research, 55*, 695–708.
Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant validity testing in marketing: an analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science, 44*, 119–134.
Wold, H. O. A. (1982). Soft modeling: The basic design and some extensions. In K. G. Jöreskog, & H. O. A. Wold (Eds.), *Systems under indirect observations: Part II* (pp. 1–54). Amsterdam: North-Holland.
Wold, H. O. A. (2006). *Partial least squares. In encyclopedia of statistical sciences* (Vol. 9). John Wiley & Sons, Inc.
Wold, S., Sjöström, M., & Eriksson, L. (2001). PLS-regression: A basic tool of chemometrics. *Chemometrics and Intelligent Laboratory Systems, 58*, 109–130.
Wright, R. T., Campbell, D. E., Thatcher, J. B., & Roberts, N. (2012). Operationalizing multidimensional constructs in structural equation modeling: Recommendations for IS research. *Communications of the Association for Information Systems, 30*, 367–412.

Nicole Franziska Richter
University of Southern Denmark, Denmark

E-mail addresses: nicole_richter2001@yahoo.de, http://www.sdu.dk/en/.

Gabriel Cepeda
Universidad de Sevilla, Spain
E-mail addresses: gabi@us.es, http://www.us.es/acerca/directorio/ppdi/personal_6194.

José Luis Roldán
Universidad de Sevilla, Spain
E-mail addresses: jlroldan@us.es, http://personal.us.es/jlroldan/Sitio_web/Index.html.

Christian M. Ringle*
Hamburg University of Technology (TUHH), Germany
University of Newcastle, Australia

* Corresponding author. Hamburg University of Technology (TUHH), Institute of Human Resource Management and Organizations (W-9), Am Schwarzenberg-Campus 4, 21073 Hamburg, Germany. Tel.: +49 40 42878 4419; fax: +49 40 42878 4471.

E-mail addresses: ringle@tuhh.de, http://www.tuhh.de/hrmo/team/prof-dr-c-m-ringle.html (C.M. Ringle).

31 July 2016
Available online xxx