Editorial
Partial Least Squares: The Better Approach to Structural Equation Modeling?

With the ever-increasing acceptance of the need to empirically validate theories in the social science disciplines (e.g., Sheth, 1971), data and multivariate analysis techniques (e.g., Hair et al., 2010; Hair et al., 2011b; Mooi and Sarstedt, 2011) play a central role in today’s research. The evolution of structural equation modeling (SEM) methods is perhaps the most important and influential statistical development in the social sciences in recent years. SEM is a second generation multivariate analysis technique that combines features of the first generation techniques, such as principal component and linear regression analysis (Fornell, 1982, 1987). SEM is particularly useful for the process of developing and testing theories and has become a quasi-standard in research (e.g., Hair et al., 2012; Ringle et al., 2012; Shook et al., 2004; Steenkamp and Baumgartner, 2000).

When estimating structural equation models, researchers must choose between two different statistical methods: covariance-based SEM (CB-SEM; Diamantopoulos and Siguaw, 2000; Jöreskog, 1978, 1982; Rigdon, 1998) and variance-based partial least squares (PLS) path modeling, also referred to as PLS-SEM (Hair et al., 2013; Lohmöller, 1989; Rigdon, 2012; Wold, 1982). These two approaches to SEM differ greatly in their underlying philosophy and estimation objectives (Hair et al., 2011a; Henseler et al., 2009). CB-SEM is a confirmatory approach that focuses on the model’s theoretically established relationships and aims at minimizing the difference between the model-implied covariance matrix and the sample covariance matrix. In contrast, PLS-SEM is a prediction-oriented variance-based approach that focuses on endogenous target constructs in the model and aims at maximizing their explained variance (i.e., their $R^2$ value).

Although both approaches were developed at about the same time, their subsequent evolution has been far from parallel. CB-SEM experienced many methodological advances and became a broadly used approach in the social sciences (e.g., Baumgartner and Homburg, 1996; Medsker et al., 1994) due to the early development of the LISREL program in the 1970s (Jöreskog and Sörbom, 1996). In contrast, PLS-SEM software was not available for many years until Lohmöller (1984) introduced the LVPLS program in the 1980s. It was the late 1990’s when Chin’s (1998) scholarly work and the availability of graphical user interfaces for the LVPLS program (e.g., PLS Graph; Chin, 2003) stimulated key applications in marketing (e.g., customer satisfaction model studies; Fornell et al., 1996) and management information systems research (e.g., technology acceptance model studies; Gefen and Straub, 1997). Today user-friendly software tools such as SmartPLS (Ringle et al., 2005), as well as the need for more flexibility in applying statistical techniques, have revived the PLS-SEM method for applied researchers (Hair et al., forthcoming; Hair et al., 2012). New textbooks on how to use PLS-SEM (e.g., Hair et al., 2013) will further disseminate the method in university courses on the Masters and Ph.D. level, as well as in industry.

Some 35 years after Herman Wold (1974, 1975) introduced PLS-SEM as a soft modeling approach that overcomes the strict assumptions of CB-SEM, it is enjoying increasing popularity across various disciplines. In fact, PLS-SEM is experiencing widespread application as a method in both academic research and practice (e.g., Hair et al., forthcoming; Hair et al., 2012; Lee et al., 2011; Ringle et al., 2012). Likewise, methodological research has presented a wide range
of extensions that enable researchers and practitioners using PLS-SEM to provide more nuanced analyses. Some examples of these extensions are advances in multigroup analysis techniques (Sarstedt et al., 2011), PLS-SEM-specific segmentation approaches (Becker et al., forthcoming; Rigdon et al., 2010; Ringle et al., forthcoming; Sarstedt and Ringle, 2010), and methods to empirically test the mode (i.e., whether reflective or formative) of the measurement models (Gudergan et al., 2008).

Nevertheless, some researchers have questioned the technique’s value for empirical research. Criticisms range from concerns about when PLS-SEM should be applied in research practice (e.g., Evermann and Tate, 2010; Marcoulides and Saunders, 2006) to an outright denial of the method’s usefulness (e.g., Antonakis et al., 2010; Hwang et al., 2010; Rönkkö and Ylitalo, 2010). Such a dichotomy is surprising for at least two reasons. First, in the social sciences, research reality is characterized by limited sample sizes and nascent theoretical development, which often make it impossible to meet CB-SEM’s rigorous assumptions. These challenges in terms of data quality and theory may impede our understanding of phenomena by having unrealistic expectations of researchers (Sutton and Staw, 1995) and perpetuating practices that lead to Type II errors if techniques lacking statistical power fail to find a significant effect (Sosik et al., 2009). Second, there has been increased interest in and applications of formative measurement in areas as diverse as organizational behavior (Podsakoff et al., 2003), strategy (Podsakoff et al., 2006), management information systems research (Cenfetelli and Bassellier, 2009), and marketing (Jarvis et al., 2003). Even though CB-SEM can accommodate formative indicators with certain modifications, their inclusion requires imposing model constraints that often contradict theoretical considerations (e.g., Bollen and Davies, 2009; Diamantopoulos and Riefler, 2011).

In most research contexts, the consensus is that theory should guide model design rather than methodological necessities. While academic discussions about the nature and appropriateness of formative measurement are ongoing (Bagozzi, 2007, 2011; Bollen, 2007; Diamantopoulos, 2006, 2011; Diamantopoulos et al., 2008; Diamantopoulos and Winklhofer, 2001; Howell et al., 2007a,b), there is little doubt that business practice can benefit from measurements and methods that provide actionable results (Albers, 2010), especially in light of the omnipresent discussion on the practical relevance of academic research (e.g., Lehmann et al., 2011; Reibstein et al., 2009). Considering these realities, PLS-SEM plays an important role in business research and practice.

CB-SEM or PLS-SEM, which is the better approach to SEM? To make a long story short: Much has been said about the distinction between CB-SEM and PLS-SEM, their advantages and disadvantages, and the reasons why one technique should (not) be preferred (e.g., Hair et al., 2011a; Henseler et al., 2009; Jöreskog and Wold, 1982; Lu et al., 2011; Marcoulides et al., 2012). We believe that such debates are fruitful as long as they do not develop a ritualistic adherence to dogma and do not advocate one technique’s use as generally advantageous in all situations. Any extreme position that (often systematically) neglects the beneficial features of the other technique and may result in prejudiced boycott calls (e.g., Antonakis et al., 2010; Rönkkö and Ylitalo, 2010), is not good research practice and does not help to truly advance our understanding of methods (or any other subject).

In this context, researchers are well advised not to blindly accept prior research results that document the superiority of one technique over the other. For example, the study by Hwang et al. (2010) uses a simulation study to show that their new GSCA algorithm generally performs as well as, and sometimes clearly better than, PLS-SEM. In many respect, the results of PLS-SEM are not in line with the outcomes (e.g., the precision of PLS-SEM results; the relatively high statistical power with small sample sizes) of prior simulation studies such as the one presented by Reinartz et al. (2009). In his rejoinder, Henseler (2012) shows that the results presented in the JMR article by Hwang et al. (2010) are invalid due to at least two major flaws in their study and that their conclusions regarding the PLS-SEM method are thus misleading. A similar exchange of blows has recently been published by (Goodhue et al., 2012a; Goodhue et al., 2012b; Marcoulides et al., 2012).
Overall, we call for a more balanced and informed judgment of the available SEM methods. As with any multivariate analysis technique, each approach has its strengths and weaknesses. Hence, with respect to the relevant facts, every researcher must decide which method is the most appropriate in her or his particular research situation.

CB-SEM and PLS-SEM are different, but complementary, statistical methods for SEM. One method’s advantages are the disadvantages of the other and vice versa. The best arguments for this balanced and more informed position originate from the key developers of the two methods, Karl Jöreskog and Herman Wold (1982). Consequently, it is incumbent on individual researchers, editors, and reviewers to ensure the propagation of the appropriate use of SEM methods. This primarily involves understanding what the corresponding technique has been designed for and being truthful about its application.

Researchers and practitioners appreciate the various advantageous features that PLS-SEM, as a component-based approach to SEM, offers in practical applications. Although strategic management research relatively early on recognized PLS-SEM’s flexibility regarding handling various modeling problems in studies (e.g., Hulland, 1999), its usefulness is still not well established amongst many management and strategy researchers. Against this background, this Long Range Planning special issue on PLS-SEM in strategic management research and practice seeks to provide a forum for topical issues that demonstrate its usefulness in this field. Descriptions of the method, its empirical applications, and methodological advancements that increase its usefulness in research and practice are specifically emphasized. As such, the special issue aims at two audiences: academics involved in the fields of strategy and management, and practitioners such as consultants. Accordingly, theoretical, methodological, and empirical manuscripts with strong implications for strategic research and practice are included in this special issue.

Long Range Planning (http://www.journals.elsevier.com/long-range-planning/) received 41 articles for its special issue on PLS-SEM, twelve of which passed a thorough review process. We thank all the reviewers for their assistance and support in developing this special issue (see our note at the end of this editorial). The decision was made to split the special issue into one that primarily focuses on methodological issues in PLS-SEM (which is this special issue) and another that includes applications of PLS-SEM in management. The second special issue will appear in 2013.

In the lead article of this special issue, titled “The Use of Partial Least Squares Equation Modeling in Strategic Management Research: A Review of Past Practices and Recommendations for Future Applications,” Joe F. Hair, Marko Sarstedt, Torsten Pieper, and Christian M. Ringle review the use of PLS-SEM in 37 studies published in eight top-tier management journals according to dozens of relevant criteria, including the reasons for using PLS-SEM, the data characteristics, model characteristics, model evaluation, and reporting. The results not only reveal several problematic aspects of PLS-SEM use in strategic management research, but also substantiate some improvement over time. The authors find that researchers often still do not fully make use of the method’s capabilities, sometimes even misapplying it. This review of PLS-SEM applications and recommendations on how to improve its use are important to disseminate rigorous research and publication practices in the strategic management discipline.

The review substantiates that several widely cited weaknesses of PLS-SEM center on its character as a composite-based method rather than a factor-based method. In his article titled “Rethinking Partial Least Squares Path Modeling: In Praise of Simple Methods,” Edward E. Rigdon moves this discussion forward by exploring concepts from the forecasting literature which suggest that that, as a prediction tool, PLS-SEM has strengths that have not been fully appreciated. The author’s final conclusion is that PLS-SEM can move forward by embracing a wider range of composite modeling options, by fleshing out inferential tools appropriate for a composite method, and by freeing itself entirely of its heritage as “something like but not quite a factor method.” We believe that this article has the potential to terminate the seemingly never-ending debate on CB-SEM vs. PLS-SEM that has dominated much of the discussion of the PLS-SEM method in recent years. Rather than providing yet another comparative evaluation of PLS-SEM and CB-SEM, researchers should focus
on further applying and advancing the manifold methodological extensions that research has recently brought forward.

One of these extensions is the estimation of hierarchical component models that enable researchers to estimate constructs measured at several dimensions of abstraction. Hierarchical component models have become an increasingly visible approach to model complex constructs, as they allow for a more parsimonious set-up of the structural model. However, research in this field has mainly centered on hierarchical component models with reflective relationships. In their paper titled “Hierarchical Latent Variable Models in PLS-SEM: Guidelines for Using Reflective-Formative Type Models,” Jan-Michael Becker, Kristina Klein, and Martin Wetzels extend prior research by exploring approaches to estimate hierarchical component models with formative relationships. The findings from their simulation and the empirical application serve as a basis for recommendations and guidelines regarding the use and estimation of reflective-formative type hierarchical latent variable models in PLS-SEM. Considering the ever-increasing use of hierarchical component models in research (Ringle et al., 2012), this article is an important step towards improving their correct application.

Another important issue to which methodological research in the PLS-SEM field has recently paid attention, is the identification and treatment of unobserved heterogeneity that, if not handled properly, can be a major validity threat to analysis results (Becker et al., forthcoming; Rigdon et al., 2010; Rigdon et al., 2011; Ringle et al., forthcoming; Sarstedt, 2008; Sarstedt and Ringle, 2010). The article titled “Exploring Unanticipated Consequences of Strategy Amongst Stakeholder Segments: The Case of a European Revenue Service” by Kevin G. Money, Carola Hillenbrand, Jörg Henseler, and Nuno Da Camara is the first in strategic management literature to address this critical issue of unobserved heterogeneity. By applying the FIMIX-PLS segmentation method, the authors detect and explore the different stakeholder segments’ unanticipated reactions to the organizational strategy of a European revenue service. The authors also present a novel approach to assess measurement invariance in PLS multigroup analysis (Sarstedt et al., 2011). The findings suggest that individual taxpayers can be split into two equally sized segments with highly differentiated characteristics and reactions to organizational strategy and communications. This study serves as a blueprint for all future PLS-SEM studies in the strategic management field as it underlines the need to consider unobserved heterogeneity to avoid false and misleading findings and conclusions.

Another new PLS-SEM approach examines the analysis of circumplex structures. In their article, “A Model of Response Strategies in Strategic Alliances: A PLS Analysis of a Circumplex Structure,” Olivier Furrer, Brian Tjemkes, and Jörg Henseler develop and test a predictive model of alliance partners’ response strategies. They further enhance the PLS-SEM algorithm to validate the circumplex structure, which allows for assessing the effects of the antecedents of alliance partner behavior. By accounting for the circumplex structure, this study increases the predictive power of PLS path models, and thereby contributes to a better understanding of managers’ complex decision-making processes in strategic alliances. Furthermore, the authors offer methodological advances that further support the prediction-oriented character of the PLS-SEM method.

Finally, an empirical application in this first Long Range Planning special issue on PLS-SEM — “Strategic Implications for (Non-Equity) Alliance Performance” by Siegfried Gudergan, Timothy Devinney, Nicole F. Richter, and Susan Ellis — uses data from two separate cross-industry samples to analyze a theoretic framework of the key antecedents of alliance performance. The authors find that capability complementarity and investment in the alliance (i.e., via their influence on the development of competitive capabilities), as well as implementation effort are important elements that ultimately affect the success of the partnership in non-equity alliances. This study is an impressive example of how the appropriate use of the PLS-SEM method facilitates novel findings on the relationship between alliance performance and the capacity of the alliance to change and innovate in a strategically flexible manner.

We are very grateful to the reviewers who contributed their valuable time and talent to develop this special issue, and ensured the articles’ quality with their constructive comments and
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References


Biographies

Joseph F. Hair, Kennesaw State University. E-mail: jhair3@kennesaw.edu

Christian M. Ringle, Hamburg University of Technology (TUHH). E-mail: hrmo@tuhh.de

Marko Sarstedt, Otto-von-Guericke-University Magdeburg. E-mail: marko.sarstedt@ovgu.de

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