A critical look at the use of SEM in international business research

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Abstract

Purpose – Structural equation modeling (SEM) has been widely used to examine complex research models in international business and marketing research. While the covariance-based SEM (CB-SEM) approach is dominant, the authors argue that the field's dynamic nature and the sometimes early stage of theory development more often require a partial least squares SEM (PLS-SEM) approach. The purpose of this paper is to critically review the application of SEM techniques in the field.

Design/methodology/approach – The authors searched six journals with an international business (and marketing) focus (Management International Review, Journal of International Business Studies, Journal of International Management, International Marketing Review, Journal of World Business, International Business Review) from 1990 to 2013. The authors reviewed all articles that apply SEM, analyzed their research objectives and methodology choices, and assessed whether the PLS-SEM papers followed the best practices outlined in the past.

Findings – Of the articles, 379 utilized CB-SEM and 45 PLS-SEM. The reasons for using PLS-SEM referred largely to sampling and data measurement issues and did not sufficiently build on the procedure’s benefits that stem from its design for predictive and exploratory purposes. Thus, the procedure’s key benefits, which might be fruitful for the theorizing process, are not being fully exploited. Furthermore, authors need to better follow best practices to truly advance theory building.

Research limitations/implications – The authors examined a subset of journals in the field and did not include general management journals that publish international business and...
marketing-related studies. Furthermore, the authors found only limited use of PLS-SEM in the journals the authors considered relevant to the study.

**Originality/value** – The study contributes to the literature by providing researchers seeking to adopt SEM as an analytical method with practical guidelines for making better choices concerning an appropriate SEM approach. Furthermore, based on a systematic review of current practices in the international business and marketing literature, the authors identify critical challenges in the selection and use of SEM procedures and offer concrete recommendations for better practice.

**Keywords** International marketing, International business, Structural equation modelling, Covariance-based SEM, Partial least squares SEM

**Paper type** Research paper

**Introduction**

Researchers in international business and marketing face the challenge of constantly and rapidly changing research contexts owing to the growing internationalization of firms, the development of the global economy, and significant shifts in the formal and informal institutional environments. Following these changes, the international research agenda has also changed in the past few epochs: The focus from 1945 to the 1950s was on explaining foreign direct investments flows and then shifted toward the explanation of the existence, strategy, and organization of multinational firms, which was especially popular from the 1970s to the 1990s. From the mid-1980s, the development of internationalization and globalization was placed on the agenda (see Buckley, 2002). Although a large portion of the international business and marketing literature is characterized by much available expertise and prior research, studies often build on theory in progress or theorizing (i.e. expanding, modifying, and further developing existing theory). To address the changes in the international environment and the ways international business and management are conducted, researchers often make use of a broad spectrum of theoretical explanations and borrow theories from other management disciplines to explain international research problems (e.g. White et al., 2016; Seno-Alday, 2010; Buckley and Lessard, 2005; Tsui, 2007). Furthermore, over the past decades, the fluid and dynamic environment has led to increasingly complex research phenomena and models (e.g. Dunning, 2007, 2008).

Therefore, international business and marketing research requires the use of methodological approaches that are able to handle the field’s changing nature and complexity, and the resulting broad theorizing agenda (Buckley, 2002; Dunning, 2001; Sinkovics et al., 2005; Seno-Alday, 2010; Sullivan and Daniels, 2008). In selecting an analytical approach, researchers need to carefully consider the research objective, the underlying theoretical knowledge, and the existing empirical evidence.

Exploring is the first step in theory building – the step that establishes the initial link between the observations a researcher gathers about a phenomenon and a theory that describes it. Thus, if the primary objective is to develop hypotheses rather than test them, the researcher identifies and further explores the relevant and dominant effects. Such exploration-oriented approaches are not aligned with a particular theoretical basis, they are often based on several theoretical perspectives, and researchers often explain findings by (carefully) using different lenses. To address the specifics of a more exploratory approach and the increasing complexity of international business and marketing phenomena, researchers need to carefully choose an analytical technique that aligns the research objective with the amount of existing knowledge.

One of the most powerful current research methodologies is structural equation modeling (SEM), which mainly follows one of two procedures: composite-based partial least
squares SEM (PLS-SEM) (Wold, 1982; Hair et al., 2017) and factor-based covariance-based SEM (CB-SEM) (Jöreskog, 1978; Rigdon, 1998), which were developed as complementary SEM methods (Jöreskog and Wold, 1982). They differ greatly in their statistical methods, and have distinct goals and requirements (Hair et al., 2011; Henseler et al., 2009). Nonetheless, researchers have predominantly discussed PLS-SEM’s ability to mimic CB-SEM results, over the decades (Hair et al., 2012; Sarstedt et al., 2014a). Authors point out that the development of consistent PLS (PLSc) algorithms (Bentler and Huang, 2014; Dijkstra, 2014; Dijkstra and Henseler, 2015a) has the potential to fully mimic CB-SEM, thereby offering an opportunity to fill the gap between factor models and composite models. Furthermore, the development of new and better-suited criteria to assess discriminant validity (Henseler et al., 2015) or measurement invariance (Henseler et al., 2016) contributes to its ability to mimic CB-SEM. Yet, it is important to establish composite-based PLS-SEM as a distinct method (Sarstedt et al., 2014b). Rigdon (2012, 2014) advocates emancipating composite-based SEM (e.g. PLS-SEM) as a method for estimating complex cause-effect relationship models.

In general, PLS-SEM, in contrast to CB-SEM, stresses prediction and exploration, is able to handle complex models, and simultaneously relaxes the demands on data as well as the specification of relationships (e.g. Jöreskog and Wold, 1982). The procedure involves a variety of benefits that could be fruitful for international business and marketing researchers to exploit. For instance, it better serves predictive and exploratory purposes involved in situations of soft theory (Sosik et al., 2009) and is better suited to explain complex models or relationships (Fornell, 1982; Wold, 1985). The evaluation of (new) methodological approaches to address specific research problems has been the focus of international marketing and advertising research (e.g. Sinkovics et al., 2005; Henseler et al., 2009, 2012) and is a priority on the international business agenda (e.g. Dunning, 2001; Tsui, 2007): to advance the field, procedures that are able to cope with the field’s characteristics (i.e. the changing and complex research environments), and that offer support for the fields theorizing purposes, need to be identified. Our paper aims at contributing to the identification of appropriate research procedures in the field. In this vein, we reviewed six leading journals that address international business and marketing topics in particular over the past 24 years (1990-2013). We reviewed articles in terms of SEM usage in an effort to evaluate the methodological fit – the link between the research purpose and the most appropriate analytical approach.

We identified 324 articles that utilized SEM for the testing of measurement and structural models; of these, only 45 articles used the PLS-SEM approach. While other disciplines such as family business research (Sarstedt et al., 2014a, b), management information systems research (Hair et al., 2012b), marketing (Hair et al., 2012a), and strategic management (Hair et al., 2012a) show a broad and increasing use of PLS-SEM, international business research relies largely on CB-SEM. This observation is surprising, given the specifics of the international business research environment and its research agenda. Building on and extending the work of Hult et al. (2006) and Henseler et al. (2009), this paper has two objectives: First, we will analyze researchers’ justifications for their choice of analytic procedure and, particularly, whether authors are correctly applying PLS-SEM to their research problems, which is a prerequisite to contributing to theorizing in the field. Furthermore, we will evaluate whether authors are tapping the full potential of the specific benefits attributed to PLS-SEM. Second, we will outline recommendations for methodology use in the field in order to further advance research designs. As a result, our study contributes to the international business and marketing literature by providing researchers interested in adopting SEM as an analytic method with practical guidelines.
for making better choices on the appropriate SEM approach, and by offering concrete recommendations for better practice.

**The nature of research on international business**

International business is a relatively young field compared to other management areas, and its nature has changed over time (e.g. Seno-Alday, 2010; Rugman et al., 2011). Earlier studies on the nature of international business concentrated on the characteristics of firms that internationalize, compared to domestic firms. More recent studies have also examined cross-border alliances and networks of firms in order to capture the changes in the formation, range, and structure of relationships between the players involved in international business and marketing. Furthermore, researchers have shifted their focus toward the individual's role in the internationalization process and have examined the effects of international experience, personality, and skills on firms' international strategy and performance. In analyzing the way firms internationalize, earlier studies identified the opportunities and barriers that may foster or hinder firms' internationalization activities, more recent studies have investigated the speed, depth, and breadth of company internationalization (Seno-Alday, 2010). Here, specifically, the internet and accompanying technological advances as well as the acceleration of technical change in telecommunications affect firms' internationalization activities (Sinkovics et al., 2013). Streams that seek to describe the nature of the interaction between different national environments (e.g. in the form of laws, regulations, cultural norms, and values) face constant changes in both the global economy and the environment. Finally, research on internationalization's impact on business has also changed: while earlier studies predominantly analyzed the impact of international activities on company performance, more recent studies see international performance as the primary rationale behind successful internationalization. In sum, the environmental context in which international business and marketing research is conducted is constantly changing (Dunning, 2007, 2008; Aharoni and Brock, 2010), and this is reflected in the dynamics of the research questions in these fields.

An analysis of the major international business research themes and their development shows increasing complexity in the research problems and models under observation. While early research concentrated on parallel models that test the joint effect of different independent variables on a dependent variable, in the past two decades, more complex structural models have been investigated, considering the increased complexity of the research questions. Furthermore, given the ever-changing nature of the challenges that confront internationally active firms and the research questions that arise in relation to these challenges, theory in international business often develops through a funnel approach: researchers tend to start with fairly general and larger research questions that are more phenomenon driven and that become increasingly specific with the development of the theoretical underpinnings in a research area. Thus, researchers start with a fairly broad spectrum of potential theoretical explanations for a phenomenon, then narrow the focus of assessment so that a specific theoretical basis can be identified. In light of the changes in the international environment and research, prior studies argue that researchers should not only aim to confirm existing theories, but should also expand, modify, and further develop existing theory (Seno-Alday, 2010). Many scholars are also suggesting that the use of exploratory research (and qualitative methodologies) is more appropriate in these contexts (e.g. Sinkovics et al., 2005; Ghauri and Grønhaug, 2002) frequently advocating a dynamic type of theorizing that is attuned to the “progressive” interaction between theory and data (Sinkovics and Aalfoldi, 2012). Furthermore, previous research has often used theories from other
management disciplines to explain international research problems for which no specific international business theory is available (Buckley and Lessard, 2005; Tsui, 2007). While the theories borrowed from other disciplines have helped increase our understanding of certain phenomena, there is a need to develop new theories to explain emerging research questions that are specific to international business and are difficult to explain with existing theory (Griffith et al., 2008). To account for the field's dynamism and complexity, modified existing theories as well as newly developed theories need to be more process oriented and predictive (Seno-Alday, 2010). While a study's theoretical contribution is important (Bello and Kostova, 2012; Thomas et al., 2011), previous international business research may have been overly focussed on testing theory and may have neglected explorative and early theorizing research, which is important for questioning existing theories and research methods and for creating new theories and methodological approaches (Corbett et al., 2014; Dunning, 2001; Peng, 2004; Tsui, 2007).

International research would benefit from a constant process of theorizing through which researchers address changes in the environment. Both the dynamic nature of the international business and marketing field as well as the growing complexity of the phenomena under observation are challenges for the research methodology employed in this area. Scholars have identified the shortcomings of mainstream methodology relating to conducting research in this dynamic context. As Dunning (2007, p. 292) notes, “unexpected technological change, new uninsurable risks, natural disasters, increased insecurity, unanticipated shifts in ideologies and political volatility, each point to a Zeitgeist, where received scholarly wisdom and mainstream methodologies are of limited use [...].” The nature of international business research and its complexity require methodological approaches that account for the characteristics that are specific to the field, thereby enabling the advancement and further development of international business theory (Buckley, 2002; Dunning, 2001; Seno-Alday, 2010; Sullivan and Daniels, 2008). In the words of Dunning (2007, p. 295), “the beginning of any new Zeitgeist requires new vision, more understanding, more diagnostic research, more experimental methods, and more empirical evidence before it is possible to design and test new theories [...].”

**SEM in international business research**

*Which SEM procedure for which research objective?*

Confirmatory empirical research ideally proceeds from theoretical assertions on which variables explain a phenomenon, how these variables are related, and why they are causally related (see Whetten, 1989; Sutton and Staw, 1995). Theory, then, is the basis for developing a set of hypotheses (“statements about what is expected to occur”) that are empirically tested. Failing to reject these hypotheses leads a researcher to feel confident that both the hypotheses and the underlying theory are valid (see Jaeger and Halliday, 1998; Sutton and Staw, 1995). In confirmatory approaches, the relationships explored are channeled toward a theoretically specified causal model (Shmueli, 2010). However, if the objective is to generate or determine novel hypotheses in a previously unexplored field or in fields that lack solid empirical foundations and theory, predictive or exploratory research approaches are the first-order instrument. Prediction is the process of applying a statistical model to data to forecast an output value for new or future observations given their input values. In predictive approaches, exploration is “[...] used in a more free-form fashion, supporting the purpose of capturing relationships that are perhaps unknown or at least less formally formulated” (Shmueli, 2010, p. 297). Hence, the goal of predictive and exploratory research is not only found in forecasting, but also in developing new and extending existing theory. Here, theory and
hypotheses are gleaned from the data analyzed and represent the inferences of the conducted research (see Jaeger and Halliday, 1998). Weick (1995) posits that theory is a continuum of theorizing (see also Runkel and Runkel, 1984), that is, a process or interim struggle of researchers inching toward strong theory. It “[…] consists of activities like abstracting, generalizing, relating, selecting, explaining, synthesizing, and idealizing” (Weick, 1995, p. 389). The progress made in this process can manifest in research outcomes such as substantiated hypotheses, which provide direction. Hence, in a situation of strong theory, confirmatory, or explanatory (also called hard) modeling is advised, whereas in a situation of weak theory, exploratory, or predictive (also called soft) modeling is a fruitful path (Sarstedt et al., 2014a, b). In the context of SEM, these different modeling purposes (among other aspects) differentiate CB-SEM from PLS-SEM (Hair et al., 2011; Shmueli, 2010; Sosik et al., 2009).

In CB-SEM, a strong theory drives model development; hence, all known theoretical relationships need to be modeled. CB-SEM estimates model parameters so that the difference between the empirical covariance matrix and the covariance matrix determined by the theoretical model is minimized. Furthermore, fit statistics are computed to evaluate the extent to which the empirical data fit the theoretical research model. Thus, the theoretical model’s correctness is the basic assumption that underlies the approach (Fornell, 1987). Still, CB-SEM is viewed as the more appropriate approach by many authors when there is a solid or strong theoretical foundation for the proposed research model, as it was designed exactly for such explanatory purposes (the question whether PLS-SEM is able to mimic CB-SEM results has been the focus of past discussions, and we will not address it here) (e.g. see Reinartz et al., 2009; Rigdon, 2012, 2014; Sarstedt et al., 2014a, b; these authors promote the use of PLS-SEM for both predictive and explanatory purposes).

However, in the stage of theory development or theorizing, a detailed and unambiguous specification of a research or causal model with unambiguous and invariant structural relationships (and parameters) might not be possible. In such situations, a soft-modeling approach can be useful. In soft modeling, the focus is on the best prediction of a specific set of structural relationships between the variables of interest (Sosik et al., 2009). This was stressed by Wold (1985), who originally designed the method for research situations that are simultaneously data-rich and theory-soft. Wold (1985) envisioned a discovery-oriented approach: Rather than committing to a specific model a priori and framing the statistical analysis as a hypothesis test, he imagined researchers estimating numerous models in the course of learning something about the data and the phenomena. PLS-SEM proves particularly valuable for such predictive and exploratory purposes, because the extraction of latent variable scores in conjunction with the explanation of a large percentage of the variance in the indicator variables are useful for accurately predicting individuals’ scores on the latent variables (Anderson and Gerbing, 1988; Wold, 1982, 1985). The latter aspect allows PLS-SEM to become a useful method for predictive modeling. Publications such as Evermann and Tate (2016) and Becker et al. (2013) follow Rigdon’s (2012, 2014) call to further develop PLS-SEM into this direction and thereby to emancipate itself from CB-SEM (Sarstedt et al., 2014a, b). Furthermore, PLS-SEM is better suited to explain complex models or relationships (Fornell, 1982; Wold, 1985). In CB-SEM, model complexity affects various goodness-of-fit measures, such as the chi-square value. For instance, the chi-square value decreases when parameters (or complexity) are added to the model. Thus, a good model fit (represented by a smaller chi-square value) may result either from a correctly specified model or from high model
complexity (Anderson and Gerbing, 1984). As a result, an inferior model fit may result either from an incorrectly specified model or from low model complexity. In PLS-SEM, complexity is not problematic, as long as the sample is of sufficient size. PLS-SEM’s superiority in terms of prediction and exploratory research has been validated in a simulation study by Reinartz et al. (2009), that confirms “[…] the widespread belief that PLS is preferable to maximum-likelihood-based CB-SEM when the research focus lies in identifying relationships (i.e. prediction and theory development) instead of confirming them” (Reinartz et al., 2009, p. 340). Hence, authors are advised to make use of the benefits offered by PLS-SEM in research situations characterized by theorizing and prediction-oriented goals rather than by strong theory (e.g. Sarstedt et al., 2014a, b).

In Table I, we summarize these benefits according to the stages of the empirical research process (following Churchill, 1995); we also highlight the following advantages of special relevance during the problem definition or research goal stage.

<table>
<thead>
<tr>
<th>Stages in empirical research (Churchill, 1995)</th>
<th>Processes peculiar to theorizing (Weick, 1995)</th>
<th>… might be supported by the following characteristics of PLS-SEM (e.g. see Henseler et al., 2009, 2014; Hair et al., 2011, 2012, 2013, 2014; Sarstedt et al., 2014a, b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem definition and research goal</td>
<td>Generalizing findings to other research areas</td>
<td>(1) Test for the predictive relevance of hypothesized relationships in different research areas (prediction orientation of PLS-SEM, optimal for prediction accuracy, for establishing models with high predictive power, and short distance to practice)</td>
</tr>
<tr>
<td></td>
<td>Selecting from different approaches and synthesizing different approaches</td>
<td>The assessment of predictive power allows one to select from competing models, and points to room for improvement in terms of practical relevance (i.e. (2) test and improve existing models by synthesizing different approaches); PLS-SEM’s ability to test more complex models can help researchers to explore and (3) uncover new causal relationships that had previously been overlooked</td>
</tr>
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<td></td>
<td>Explaining new relationships</td>
<td>PLS-SEM tools for multigroup analyses or more explorative or prediction-oriented procedures such as FIMIX-PLS or PLS-POS help to (4) identify relevant contextual factors that define relevant segments or subgroups</td>
</tr>
<tr>
<td></td>
<td>Relating findings to contextual factors</td>
<td>(5) The data are nonnormal</td>
</tr>
<tr>
<td>Data collection and preparation</td>
<td>Collection a variety of data with constructs that are theoretically less-clearly defined</td>
<td>(6) The analysis draws on secondary data</td>
</tr>
<tr>
<td>Data analysis</td>
<td>Analysis of a variety of often complex research models</td>
<td>(7) The causal model comprises many constructs, path relationships, and indicators, advanced elements such as moderator variables or hierarchical components, and formatively measured constructs</td>
</tr>
</tbody>
</table>

Table I: PLS-SEM benefits in the process of theorizing
(which relates to all subsequent stages): prediction: if the research objective is to establish models that have high predictive power and thereby exhibit a short distance between theory and practice; improve and further develop existing models with regard to their practical relevance. The assessment of predictive power allows one to select from competing models. The goal is to establish suitable theories using explanatory models that have predictive power and are therefore relevant. If an explanatory model has relatively low predictive power, it offers substantial room for scientific development, aimed at improving its theoretical and practical relevance; uncover new causal relationships by testing more complex models. PLS-SEM, which is less subject to complexity limitations than CB-SEM, can assist researchers with exploring and uncovering new causal relationships that have previously been overlooked, ignored, or neglected. By capturing underlying complex patterns and relationships, predictive modeling can reveal directions for further developing existing explanatory models; test for the existence of unobserved heterogeneity: PLS-SEM offers comfortable tools such as FIMIX-PLS (e.g. Hahn et al., 2002; Sarstedt and Ringle, 2010; Sarstedt et al., 2011a), PLS prediction-oriented segmentation (PLS-POS) (e.g. Becker et al., 2013) or PLS genetic algorithm segmentation (PLS-GAS) (Ringle et al., 2013, 2014) for exploratory purposes in terms of considering (observed but especially) unobserved heterogeneity (i.e. if different parameters are likely to occur in different subpopulations in the data) (Henseler and Chin, 2010; Rigdon et al., 2010; Sarstedt et al., 2011a, b; Becker et al., 2013).

The use of SEM in past international business research
To assess the use of the different SEM approaches in international business, we mainly build on and extend the work of Hult et al. (2006), who identified 148 articles (from ten journals) that utilized CB-SEM and investigated CB-SEM usage in the field. Their results show that, in 43 studies, research models were respecified, yet in the majority of cases without theoretical justifications for the changes made and without explicitly noting the exploratory nature of their respecifications. We concentrate on the use of the two SEM approaches in six leading journals that address mostly international business topics (we exclude general management research journals, since our focus is on international business). We identified the relevant studies as follows: First, we examined the citations in Hult et al. (2006). Second, we searched the issues of the six journals (see Table I) from 1990 to 2013. We also conducted a manual search of in-press articles in these journals. Keywords used included confirmatory factor analysis, SEM, partial least squares, PLS, and path model; variations and combinations of various keywords were used. We identified 425 articles that utilized SEM approaches for the testing of measurement and structural models; in one article artificial neural networks were used (Garbe and Richter, 2009) and we excluded it from the further review. While CB-SEM has often been used during the past decades (379 of the articles we identified used CB-SEM), and its use is growing year-on-year, very few of the researchers in our sample had used PLS-SEM (45 articles), and it is only very recently that the number of such published studies has increased (see Tables II and III).

Two independent coders with in-depth knowledge of the international business literature and the two SEM approaches reviewed and evaluated the identified studies for study characteristics, the way each SEM approach was utilized and, if provided, the justification for the utilized SEM method. To assess intercoder reliability, the two coders reviewed a random sample of 100 studies, representing more than 23 percent of...
the total number of articles. The codings were compared, and intercoder reliability was calculated using Cohen’s $\kappa$ coefficient (Cohen, 1960). Overall intercoder agreement was 0.78 – above the recommended threshold of 0.70. All coding was done separately, and any disagreements were analyzed and discussed between the coders.

Of the 45 studies to use PLS-SEM, two utilized it to build formative constructs that were later used in regression models. The remaining 43 studies applied PLS-SEM to calculate the inner (structural) as well as the outer (measurement) models. Of these 43 studies, four did not provide reasons for their methodological choice. The studies that

<table>
<thead>
<tr>
<th>Journals</th>
<th>CB-SEM (of which 144 focus on factor analyses)</th>
<th>PLS-SEM (of which two focus on factor analyses)</th>
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</thead>
<tbody>
<tr>
<td>International Business Review</td>
<td>70</td>
<td>15</td>
</tr>
<tr>
<td>International Marketing Review</td>
<td>99</td>
<td>4</td>
</tr>
<tr>
<td>Journal of International Business Studies</td>
<td>108</td>
<td>7</td>
</tr>
<tr>
<td>Journal of International Management</td>
<td>24</td>
<td>4</td>
</tr>
<tr>
<td>Journal of World Business</td>
<td>52</td>
<td>8</td>
</tr>
<tr>
<td>Management International Review</td>
<td>26</td>
<td>7</td>
</tr>
</tbody>
</table>

<table>
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<tr>
<th>Years</th>
<th>CB-SEM (of which 144 focus on factor analyses)</th>
<th>PLS-SEM (of which two focus on factor analyses)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990-1994</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>1995-1999</td>
<td>28</td>
<td>2</td>
</tr>
<tr>
<td>2000-2004</td>
<td>70</td>
<td>3</td>
</tr>
<tr>
<td>2005-2009</td>
<td>131</td>
<td>8</td>
</tr>
<tr>
<td>2010-2013</td>
<td>148</td>
<td>31</td>
</tr>
<tr>
<td>Total</td>
<td>379</td>
<td>45</td>
</tr>
</tbody>
</table>

Table II.
Number of studies that applied CB-SEM or PLS-SEM

Table III.
Overview of PLS-SEM papers reviewed
did provide a reason always gave more than one. The most common justifications were small sample size (56 percent, 24 out of 43), data distribution (47 percent, 20 out of 43), exploratory investigation and theory development (40 percent, 17 out of 43), use of formative indicators (35 percent, 15 out of 43), explanatory power and predictive performance (30 percent, 13 out of 43), model complexity (28 percent, 12 out of 43), measurement scale (16 percent, 7 out of 43), assessment of reliability and validity (5 percent, 2 out of 43), and assessment of relationships between constructs (5 percent, 2 out of 43). Overall, these findings suggest that international business researchers’ PLS-SEM usage is largely determined by the characteristics of the data (small sample sizes and the non-normal data distribution) and the measures utilized (formative measures) and, to a lesser degree, by research objectives that champion the characteristics of the PLS-SEM approach (exploratory investigation and theory development as well as explanatory power and predictive performance).

Of the 379 studies to use the CB-SEM approach, 235 (62 percent) utilized it to assess the measurement model as well as the structural model, and 144 (38 percent) used it for the measurement model only (i.e., performed a confirmatory factor analysis) and chose a different analytic approach to test the proposed hypotheses. Of the studies to utilize CB-SEM to test a structural model, the overwhelming majority provided no reason for this methodological choice (64 percent, 150 out of 235). In only a small number of papers did the authors directly state that CB-SEM is a useful tool for testing theory and that they were employing it for this reason (13 percent, 31 out of 235). Other reasons to justify methodological choices were: simultaneous testing of various relationships (11 percent, 25 out of 235), measurement errors (8 percent, 18 out of 235), use of latent constructs with multiple indicators (7 percent, 17 out of 235), a complex model (5 percent, 11 out of 235), testing of mediation (4 percent, 10 out of 235), comparison of different groups (6 percent, 13 out of 235), and simultaneous assessment of the measurement model (3 percent, 8 out of 235). Thus, only a few studies explicitly justified CB-SEM usage by its ability to test theory-based hypotheses. Given the high number of different research questions examined, we can only speculate that, for a relevant number of studies, PLS-SEM might have been a better methodological choice given an often-immature theoretical basis for various international business research themes and the changing, dynamic nature of the international context.

The testing and establishment of measurement invariance by means of CB-SEM applications are described in different management research fields that investigate international phenomena, such as international human resources management (e.g., Cascio, 2012; Nimon and Reio, 2011; Schmitt and Kuljanin, 2008), international marketing (e.g., He et al., 2008; Steenkamp and Baumgartner, 1998), international organizational behavior (e.g., Tsui et al., 2007), and international business (e.g., Hult et al., 2006; Diamantopoulos and Papadopoulos, 2010), but only one study mentions this as the reason for CB-SEM usage.

Do researchers follow PLS-SEM application guidelines?
Methodological reviews that outline PLS-SEM best practices have evolved in various management disciplines, such as accounting (e.g., Lee et al., 2011), management information systems research (e.g., Hair et al., 2012b), marketing (e.g., Hair et al., 2012a; Henseler et al., 2009), operations management (e.g., Peng and Lai, 2012), and strategic management (e.g., Hair et al., 2012a). We will refer to the guidelines outlined in Hair et al. (2012a) to assess past PLS-SEM applications in international business research. We provide a full overview in Table IV. We will now highlight the aspects that need improvement.
Data characteristics

Sample size  
Guideline: ten times rule: the minimum sample size should be equal to the larger of the following: (1) 10 × the largest number of formative indicators used to measure one construct and (2) 10 × the largest number of structural paths directed at a particular latent construct in the structural model (Barclay et al., 1995) 
Compliance: all studies except for one complied with this rule. Sample sizes ranged from n = 38 to n = 5,191; in most cases, the rule was easily surpassed

Holdout  
Guideline: 30% of original sample (Hair et al., 2010) 
Compliance: 1 out of the 43 studies reviewed used a holdout sample

Distribution  
Guideline: robust when applied to highly skewed data, but skewness and kurtosis should be reported (Reinartz et al., 2009) 
Compliance: 20 out of 43 studies referred to this benefit of PLS-SEM; in 7, the authors mentioned that their data were not normally distributed; 1 provided information on skewness and kurtosis

Measurement (models)

Description  
Guideline: include a complete list of indicators (including scales) in the appendix 
Compliance: in 10 of the 43 studies analyzed, this information was not provided

Scales  
Guideline: use single-item measures only if applying a small sample (n < 50), if expecting weak effect sizes (cross-item correlations < 0.3), and if items are highly homogeneous (inter-item correlations > 0.8, Cronbach’s α > 0.9) and semantically redundant (Diamantopoulos et al., 2012) 
Compliance: 20 out of 43 papers referred to single-item measures; 4 out of these 20 studies lacked a complete description; 13 had samples sizes between n = 68 and n = 5,919 (i.e. single-item measures were not the first-choice instrument)

Mode  
Guideline: follow design rules (e.g. by Jarvis et al., 2003) and substantiate measurement mode (by using CTA-PLS) (e.g. Diamantopoulos et al., 2008) 
Compliance: 32 did not comment on the measurement modes used

Outer model evaluation: formative

16 studies applied formative measurement models

Indicator contribution  
Guideline: report indicator weights. Report t-values, p-values, or standard errors 
Compliance: 8 studies reported indicator weights, but only 4 reported information on the weights’ significance levels

Multicollinearity  
Guideline: report VIF, tolerance, or condition index 
VIF < 5/tolerance > 0.2; condition index < 30 (Hair et al., 2011) 
Compliance: 8 studies reported the VIF, and all of these met the guideline of a VIF < 5; no study referred to the condition index

Outer model evaluation: reflective

41 studies applied reflective measurement models

Indicator reliability  
Guideline: report standardized indicator loadings; acceptable loadings: ≥ 0.4 in exploratory, ≥ 0.7 in all other studies (Hulland, 1999) 
Compliance: in 31 studies, loadings were fully reported; in 9, all loadings were ≥ 0.7; in 15 studies using PLS-SEM for exploratory purposes, all loadings were ≥ 0.4; in 5 studies, all loadings were ≥ 0.4 but < 0.7, although exploration was not envisaged; finally, in 4 studies claiming to pursue an exploratory research objective, loadings were below 0.4

Internal consistency  
Guideline: do not use Cronbach’s α; report composite reliability – acceptable values: ≥ 0.6 in exploratory research; ≥ 0.7 in all other studies (Bagozzi and Yi, 1988) 
Compliance: 36 studies referred to internal consistency reliability; in 5, this reference was only made in the text, without the provision of numbers; 11 studies referred to α only (in 7, α was ≥ 0.7; in 4 studies, 2 of which had an exploratory focus, it was ≥ 0.6); 20 studies provided information on the composite reliability (all were ≥ 0.7)
Data characteristics

Although small sample size is a popular argument for choosing PLS-SEM in the papers we identified, the average PLS-SEM sample in our international business studies set is \( n = 354 \), clearly exceeding those in marketing research (5 percent trimmed mean: \( n = 211 \)) and CB-SEM studies (mean \( n = 246 \)) (see Hair et al., 2012a; Shah and Goldstein, 2006). In most studies, the minimum sample size required for the analysis (e.g. the ten times rule proposed by Barclay et al., 1995) was met. In light of these fairly high available sample sizes, authors should (and can) attribute more weight to another important requirement, namely, to evaluate their results’ robustness, authors are advised to use holdout samples (e.g. Hair et al., 2010), which was done in one study, only.

PLS-SEM proves to be robust in situations with extremely nonnormal data distributions (e.g. Cassel et al., 1999; Reinartz et al., 2009). Nonetheless, highly skewed data inflate (bootstrap) standard errors and reduce statistical power (Chernick, 2008). In other words, at the very least, reporting information on the data distribution is advised. In total, 20 of the 43 studies referred to the benefit of PLS-SEM of being less-demanding concerning data distribution. In seven studies, the authors later mentioned that their data were not normally distributed, but only one set of authors provided information on the skewness and kurtosis of their data. This is also a concern in other fields (see the assessment of PLS-SEM in marketing research by Hair et al., 2012a) and holds much room for improvement.

Measurement models

PLS-SEM estimates formative constructs without an error term. The establishment of an acceptable measurement validity level before analyzing structural relationships is

| Convergent validity | Guideline: report AVE; acceptable values: \( \geq 0.5 \) (Bagozzi and Yi, 1988) ±
| Disciminant validity | Guideline so far: report Fornell and Larcker (1981) criterion: each construct’s AVE should be higher than its squared correlation with any other construct. Report cross-loadings: each indicator should load highest on the construct it is intended to measure (e.g. Chin, 1998b) ±
| | Compliance: 33 studies reported information on the AVE (2 with exceptions); in 29 studies, all AVEs were provided and were on or above the acceptable value of 0.5
| | Compliance: 36 studies reported either of the above criteria; in the studies providing the required information, discriminant validity was achieved
| | Future guideline: use the heterotrait-monotrait ratio of correlations (HTMT) to assess discriminant validity in PLS-SEM as suggested by Henseler et al. (2015); acceptable value: < 0.85 ±

Inner model evaluation

\( R^2 \) Guideline: report \( R^2 \); acceptable level is context-dependent (Hair et al., 2010) +

| Path estimates | Guideline: report path coefficients; report bootstrapping to assess significance; ±
| | Compliance: 41 studies reported \( R^2 \) values; on average, we found values of 0.33 (min. = 0.01; max. = 0.87); hence, on average, there were fairly weak to moderate shares of explained variance
| | Compliance: 41 studies reported path coefficients and information with which to assess their significance levels; confidence intervals were provided in only one study
| Effect size \( f^2 \) | Guideline: report \( f^2 \); 0.02, 0.15, 0.35 for weak, moderate, strong effects (Cohen, 1988) −
| | Compliance: only two papers reported the (fairly moderate to strong) effect size ±

Notes: −, Poor compliance; ±, average compliance; +, good compliance with guidelines
Sources: Own table, based on the basic guidelines outlined in Hair et al. (2012a)
therefore essential. Ultimately, the appropriateness of the formative construct(s) is determined theoretically. Hence, a complete list of indicators (including scales) should be provided. In more than 20 percent of the studies, information on the indicators (and scales) used was not provided. In 16 articles, formative measurement models were applied, but seldom individually (one study) and most often in combination with reflective measurements (15 studies). Here, researchers should follow the measurement mode design rules that have been outlined (e.g. by Jarvis et al., 2003; or Mackenzie et al., 2011) and substantiate the formative vs reflective mode by using confirmatory tetrad analyses as an additional statistical test procedure (e.g. Bollen and Ting, 1993; Diamantopoulos et al., 2008; Gudergan et al., 2008). The overwhelming majority of studies did not further discuss the chosen mode: 32 papers did not comment further on the (reasons why) modes (were) used. Yet, 10 of the 11 studies that did explain their measurement models were published in 2010 or later, pointing to an improvement over time.

If a construct’s scope is narrow, unidimensional, and unambiguous for the respondents (both in terms of the object and its attribute), carefully crafted single-item measures might work as well as multi-item measures (e.g. Sackett and Larson, 1990; Bergkvist and Rossiter, 2007; Mooi and Sarstedt, 2011; Diamantopoulos et al., 2012). Although PLS-SEM is not restricted to multi-item measures for reflective constructs, the utilization of single items is contrary to its notion of consistency. Only with a reasonable number of indicators per construct and sufficient loadings does PLS-SEM yield acceptable parameter estimates when the sample size is restricted (as shown by Reinartz et al., 2009). Of the sample we studied, 20 papers referred to single-item measures; 13 out of these 20 papers enabled further evaluations by providing the necessary indicator data – without judging the operationalization in terms of content, we argue that single items should be used with caution (Hair et al., 2012a) and recommend that researchers follow the guidelines provided by Diamantopoulos et al. (2012).

**Evaluation of results**

To understand an indicator’s importance, indicator weights and their significance (i.e. \(t\)-values, \(p\)-values, or standard errors from resampling procedures) need to be reported and evaluated. Eight out of the 16 studies that applied formative measurements reported weights, but only four provided information on significance levels. Researchers should also examine the extent of (redundancy or) multicollinearity between a construct’s indicators (the variance inflation factor (VIF)) and the condition index are best practices (see Hair et al., 2011, 2012a). Eight studies reported the VIF; all of these met the threshold (< 5). However, the condition index was not referred to. The evaluation of formative measurement models therefore needs to be enhanced.

Reflective measurement models should be assessed in terms of the reliability of the indicator variables (Hulland, 1999): In 76 percent of studies, indicator loadings were fully reported, and in 46 percent, these loadings met the critical values for supporting reliability. Furthermore, we recommend that authors refer not only to Cronbach’s \(\alpha\) but also to composite reliability for evaluating the reliability of each construct’s composite (Bagozzi and Yi, 1988). Of the studies, 88 percent referred to this criterion; in 12 percent, a reference was made in the text without numbers being provided; 27 percent referred to \(\alpha\) only, and 49 percent provided information on composite reliability (all meeting the desired threshold). Furthermore, models need to show convergent validity; that is, the latent variable should explain more than 50 percent of its indicators’ variance (AVE) (Bagozzi and Yi, 1988). Of the studies, 81 percent reported the AVE, and nearly all
AVEs met the acceptable level. Finally, for reviewing the discriminant validity, two rules are relevant: each latent variable's AVE should be greater than its squared correlation with any other construct (see Fornell and Larcker, 1981), and an indicator's loading with its associated latent construct should surpass its loadings with all the remaining latent variables (cross-loadings) (Chin, 1998b; Grégoire and Fisher, 2006). Of the studies, 88 percent reported either of the above criteria, and discriminant validity was achieved therein. Future publications of PLS-SEM studies should use the new heterotrait-monotrait (HTMT) ratio of correlations for assessing discriminant validity in PLS-SEM (see Henseler et al., 2015). While the Fornell-Larcker criterion and the assessment of cross-loadings often fail in detecting discriminant validity problems, the HTMT performs as expected in most situations analyzed in the simulation study by Henseler et al. (2015). In sum, reflective measurements would also profit from increased caution in the evaluation and reporting of key quality criteria.

Authors comply with the evaluation criteria for assessing the structural model's quality, in terms of share of explained variance of the endogenous latent construct(s), i.e. $R^2$ (Hair et al., 2011), and sign, magnitude as well as significance of paths (via bootstrapping) (Chin, 1998b; Henseler et al., 2009), except for: providing confidence intervals; and effect sizes $f^2$ needed to assess the relative impact of an exogenous construct on an endogenous construct. Hence, we urge researchers to use all available quality criteria (including information on the predictive relevance $Q^2$ of the model, which we will address later), especially in light of the lack of an overall goodness-of-fit criterion. Confidence intervals provide additional information on the stability of coefficient estimates, while the added value of effect sizes $f^2$ is the potential to identify mediation effects if a high path coefficient has a low effect size $f^2$ (Hair et al., 2017).

Overall, we find that, in spite of the fact that this methodology is relatively new to the field, its application already complies with many of the basic rules to be followed. However, room for improvement remains; this will very likely also improve the quality of the results and, as a result, research and international business theorizing (also see Hair et al., 2013).

Do researchers tap PLS-SEM’s full potential?

In 25 of the PLS-SEM papers, the researchers stated that they were following a predictive or explorative goal. Hence, more than 50 percent of authors sought to take advantage of PLS's soft-modeling benefits; but did they tap these benefits' full potential?

PLS-SEM for prediction

PLS-SEM may serve as a reality check, testing whether models have practical relevance. In its pure form, authors performing a reality check would apply a theoretical model for which explanatory techniques yielded satisfying results, to one or more samples, to test its predictive relevance. None of the studies analyzed proceeded in this way. Besides referring to the $R^2$ results as a measure of a model's predictive capabilities, focussing on in-sample prediction rather than out-of-sample prediction, the predictive relevance $Q^2$ and the relative predictive relevance $q^2$ represent another option for assessing a model's practical relevance (Chin, 1998b; Hair et al., 2017). These criteria build on the blindfolding procedure (see Hair et al., 2017), which systematically deletes some data points and then uses the remaining data and the PLS path model estimates to predict the omitted data. The difference between the predicted and the true omitted value allows for determining the model's predictive relevance.
We found that 28 percent of articles provided information on their model’s predictive relevance (e.g. as given in Singh et al., 2006), but none of the articles provided information on relative predictive relevance (see Table V).

In contrast, we found authors who referred to different samples to assess the predictive relevance of their findings (e.g. Acedo and Jones, 2007; Lam et al., 2012). For instance, Lam et al. (2012), emphasizing prediction purposes, tested their proposed model in different subsamples: “The country-specific results allow us to test the predictive validity of the proposed framework in 15 different countries” (Lam et al., 2012, p. 316). Likewise, Acedo and Jones (2007) stated that, to test their model’s predictive relevance, they analyzed three samples. Venaik et al. (2004) referred to predictive relevance in terms of testing different operationalizations of variables, that is, they compared measurement models in terms of their predictive power. All these authors referred to their models’ $R^2$ values (and not to the $Q^2$ values) in order to evaluate the predictive relevance level (other authors also referred to the path coefficients in order to evaluate a construct’s predictive relevance; e.g. see Navarro et al., 2010).

**PLS-SEM for improving existing theories**

PLS-SEM can also be applied to improve and further develop existing models concerning their practical relevance, via model respecifications, which has some overlap with the

<table>
<thead>
<tr>
<th>Exploitation of PLS-SEM benefits</th>
<th>Guideline</th>
<th>Compliance</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prediction</td>
<td>(1) Report results of predictions conducted in one or more samples.</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Improve existing models</td>
<td>(1) Respecify models (by adding or removing paths to or from an originally proposed model); (2) base respecifications on theoretical justifications; (3) cross-validate a respecified model (e.g. MacCallum et al., 1993; Hult et al., 2006; Anderson and Gerbing, 1988; Chin, 1998a)</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Uncover new relationships</td>
<td>(1) Make use of PLS-SEM’s capacity to estimate more complex models (e.g. Sarstedt et al., 2014a)</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Uncover heterogeneity</td>
<td>(1) Uncover heterogeneity via (1) PLS-SEM multigroup analyses (e.g. Sarstedt et al., 2011a), (2) FIMIX-PLS (e.g. Sarstedt et al., 2011a, b), and (3) POS (e.g. Becker et al., 2013)</td>
<td>±</td>
<td>±</td>
</tr>
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</table>

**Table V.**

Exploitation of PLS-SEM benefits

**Notes:** –, Poor compliance; ±, average compliance; +, good compliance with guidelines
idea of testing competing models. A respecification is understood as adding or removing paths to or from an originally proposed model to better fit the data. Such procedures may be valuable for international business researchers, given the field’s relative youth (Hult et al., 2006). Hult et al. (2006) outline that “[…] for any given theoretically sound model, there may be other “competing” models that demonstrate equivalent goodness-of-fit statistics that incorporate […] alternative relationships between latent variables. […] Because possible alternative models may be very different from the theoretical model under examination, the conclusions drawn when only one model is considered may be called into question” (p. 402). In total, 13 of our PLS-SEM papers mentioned and tested competing models (e.g. Gammelgaard et al., 2012; Nielsen and Gudergan, 2012; Obadia, 2013). The number of competing models tested varied as much (from 1 over 9 to “a series of”) as the approaches used (e.g. a full model to a control or naïve model (e.g. see Engelen, 2010; Venaik et al., 2005) and the reasons for doing so. For instance, Gammelgaard et al. (2012) tested three models – one main model against two alternative models – because they had obtained mixed theoretical and empirical results for the relationships they were examining. Fey et al. (2009) argue that, while they had theoretically justified their main model, one could posit slightly different relationships. They subsequently showed that (five) variations of their causal relationships (e.g. additional paths) did not significantly improve the main model’s statistical power and concluded that their main model was at least as good as the alternative ones. Nielsen and Gudergan (2012) raised concerns about structural and measurement model misspecification in SEM, and recognized the possibility of estimating misspecified models in spite of a thorough advance development of the structural and measurement models. Accordingly, they considered several alternative model estimations to determine whether variations in their measurements (e.g. reflective or formative modes, a combined construct instead of individual performance constructs, single vs multiple items for measuring performance) or structural characteristics (e.g. direct vs indirect effects) would provide further insights. After comparing the models based on PLS’s evaluation criteria, they concluded that possible misspecifications did not appear to have biased their insights.

In addition to the above, authors might refer to more exploratory model respecifications, i.e. the modification of models in terms of adding or removing paths to achieve a better fit to the data. We identify five studies that fall into this category. To become successful, a respecification needs to follow certain procedures (see the critical comments in MacCallum et al., 1993): First, authors are encouraged to base any changes they make on theoretical justifications, which avoids capitalizing solely on the idiosyncrasies in a specific dataset (see Anderson and Gerbing, 1988; Chin, 1998a). Furthermore, a respecified model needs to be cross-validated using further samples or statistical criteria (e.g. $Q^2$) before theoretical inferences can be drawn (see Chin, 1998a).

To evaluate the use of respecifications, we refer to the criteria outlined in Hult et al. (2006): First, we ask whether authors note the exploratory nature of the model respecification and whether they cite theory as a justification for the changes made. Ciabuschi et al. (2012) as well as Ciabuschi et al. (2011) followed a partly exploratory approach, dropped insignificant links from the first estimation, and re-estimated the simplified model. Alpert et al. (2001) compared the results of their hypothesized smaller model to a full model covering all possible direct relationships. Lew et al. (2013) tested an alternative relationship without a deeper discussion of the underlying theoretical basis. Raman et al. (2013) tested different models to clearly identify the relationships in the proposed mediational chain. Overall, authors did not comment further on the reasons for respecifying models, nor did they note the exploratory nature of this
process. Second, we evaluate whether changes made are cross-validated with another sample or by reference to statistical criteria ($Q^2$). None of the studies reviewed (neither the authors testing competing models, nor the authors respecifying their models in the course of the analysis) performed cross-validation using further samples. However, four out of the five studies that used model respecifications refer to statistical criteria for the purpose of cross-validation.

In this context it is important to note that Henseler et al. (2014) suggested the use of the standardized root mean square residual for PLS-SEM. This criterion (i.e. the root mean square discrepancy between the observed correlations and the model-implied correlations; Hu and Bentler, 1998) allows to identify model misspecification, which may require a model respecification, and to determine model fit (e.g. for comparing alternative models). In the latter case, the new PLSc algorithms (Bentler and Huang, 2014; Dijkstra, 2014; Dijkstra and Henseler, 2015b) are better suited for model estimations since they offer better suited options of including global goodness-of-fit indices (Dijkstra and Henseler, 2015a).

**PLS-SEM for uncovering new causal relationships**

PLS-SEM offers increased potential to uncover new causal relationships, for instance by applying complex models. By capturing underlying complex patterns and relationships, predictive modeling can reveal directions that can be taken to further develop existing explanatory models. On average, the sample PLS-SEM papers involved models with seven latent constructs, nine paths, and 25 indicator variables. Thus, the complexity of the PLS-SEM models applied in international business seems to be comparable to other fields, such as marketing research (see Hair et al., 2012a). Compared to CB-SEM studies, the model complexity is much higher: Shah and Goldstein’s (2006) review of CB-SEM studies reveals that, in CB-SEM, on average five latent variables and 16 indicators are used (the authors do not provide the number of paths, but indicate that an average of 38 parameters are estimated). The authors in our sample who highlighted the pursuit of an exploratory research objective did not use more complex models. Hence, overall, the benefits of PLS-SEM for handling more complex models come into play regardless of the (possibly exploratory) research design.

**PLS-SEM for uncovering heterogeneity**

Of the studies, 14 conducted multigroup analyses in PLS-SEM. Most studies referred to either industry (Ainuddin et al., 2007; Navarro et al., 2010; Shi et al., 2010) or country (West and Graham, 2004; Lee et al., 2006; Fey et al., 2009; Gammelgaard et al., 2012), or both (Venaik et al., 2004, 2005) in order to actively split groups. Three further sets of authors built groups based on specific theoretical assumptions, such as the international market entry form (Acedo and Jones, 2007), the position of the firm in terms of cost competitiveness (Boehe, 2010), or the dependency structure in organizations (namely, the dependency on key account management) (Swoboda et al., 2012).

There are several approaches available to uncover unobserved heterogeneity in PLS-SEM and, among the established techniques, finite mixture PLS (FIMIX-PLS) has been recognized as the most valuable one (Sarstedt, 2008). While only one study referred to FIMIX-PLS, none of the studies reviewed adapted the newer explorative procedures, such as PLS-GAS (Ringle et al., 2013, 2014) and PLS-POS (Becker et al., 2013), yet. Since recent calls in publications (e.g. Becker et al., 2013)
require assessment as to whether unobserved heterogeneity is present in PLS-SEM studies, so as to avoid validity threats, we expect a much broader use of these techniques in future publications.

**Discussion and recommendations for further research**

SEM offers researchers a tool to analyze structural models that are responsive to, and capture the complexity of, the phenomena under observation in international business and marketing research. It allows researchers to simultaneously model relationships between multiple, sequential variables that are better able to explain processes than are parallel predictors, for instance in regression models. As outlined, international business research is often characterized by theorizing rather than the testing of strong theory. Therefore, SEM approaches that are particularly suited to these purposes should be utilized. PLS-SEM is a useful tool for identifying and establishing relationships between constructs, and for developing explanations for these relationships. That is, it is a useful tool for theorizing in management research in general (Hair et al., 2017) and in the different management disciplines, such as family business research (Astrachan et al., 2014; Sarstedt et al., 2014a, b), operations management (Peng and Lai, 2012; Roberts et al., 2010), organization research (Sosik et al., 2009), and accounting (Lee et al., 2011).

Consequently, the PLS-SEM approach is deemed very appropriate to the huge amount of research on international business and marketing that is based on fairly soft theory. The majority of studies that apply SEM in this field apply CB-SEM. In our review of six leading journals focussing on international research aspects over 24 years, we found that 89 percent of the studies applied CB-SEM. This is surprising, given the character of the international research context. Because the decision to go with CB-SEM was in most cases (in 64 percent of the studies) not further commented on, or not specific to CB-SEM as opposed to PLS-SEM (e.g. the use of latent constructs, a complex model), we can only speculate that this might be due to the stronger distribution and longer history of CB-SEM’s application in the social sciences.

The studies referring to PLS-SEM provided better reasons for their methodological choices, and the justifications largely referred to sampling – although we did find, in line with previous studies (Brock, 2003; Zhan, 2013), that sample size was often not the limiting factor in international business research; instead, data and measurement issues were (e.g. data distribution, formative constructs, and measurement scales). Our review showed that PLS-SEM usage is to a smaller degree driven by research objectives championing the characteristics of the PLS-SEM approach, stemming from PLS-SEM’s focus on prediction and soft-modeling characteristics. While a large number of international business themes are related to prediction-oriented research questions, very few of the sample studies used the approach specifically for prediction purposes. Except for the application of more complex models, the benefits of PLS-SEM do not appear to be sufficiently exploited by researchers in the field: The models’ predictive relevance were mostly not assessed, few studies used the opportunity to respecify the model in the course of their analysis. While international business and marketing research is often interested in the similarities and differences between groups, none of the sample studies referred to explorative PLS-SEM procedures for uncovering unobserved heterogeneity so as to create substantively meaningful subgroups. While international business and marketing research are not the only management domains in which sample and measurement issues are the primary reasons given for PLS-SEM usage (Hair et al., 2017), it would be particularly valuable for international business and marketing researchers to fully use the potentials of the PLS-SEM approach.
Building on these findings, we outline the following recommendations for future research: In light of the dynamic nature of international business and related developments and changes in theoretical perspectives, we advise researchers to critically assess whether a chosen analytical approach is suitable for addressing the research question, considering the amount of available empirical knowledge and the state of theory in the specific research area. A study’s research purpose and the related theoretical and empirical basis should be the primary selection criteria when choosing between PLS-SEM and CB-SEM. If the primary objective is theory development, then the PLS-SEM approach is preferable. Sample and measurement characteristics—such as sample size, distributional assumptions, measurement type, and scale—should be secondary selection criteria. Applied correctly, SEM procedures allow researchers to better understand the complex phenomena being studied in the field, and it is up to these researchers to fully leverage the specific potentials offered by the various SEM approaches. Researchers are also advised to better justify their methodological choices in light of their research problems. If the research design fits with PLS-SEM usage, we encourage researchers to be more open to more explorative techniques and designs, and to make use of the full power of PLS-SEM in the process of theorizing. Hence, we strongly encourage journal authors to clearly describe the method of analysis as well as the methodological choices made in conducting the analysis. Furthermore, we encourage journal editors and reviewers to indicate this to authors, and to enforce justification of the chosen analytical approach. Journal editors and reviewers should see exploratory research as a way to avoid theoretical stagnation. Therefore, in research areas where the theoretical and empirical basis is fairly weak, they should allow authors to ask and explore research questions, instead of positing and testing hypotheses that are embedded in fairly weak theory. Authors of an exploratory study should not be forced, in the review process, to treat their study as if it were confirmatory. PLS-SEM plays an important role as a tool in a more exploratory analytic approach, and complements the CB-SEM approach.

While we promote a stronger PLS-SEM usage in international business and marketing research, we also recommend a stricter adherence to the key guidelines or best practices outlined for conducting PLS-SEM. First, we encourage authors to more carefully discuss the chosen measurement modes; especially if applying formative measurements, models need to cover a construct’s full theoretical meaning so as to offer valid results. Concerning the application of reflective measurements, considering multiple items is a fruitful route that taps SEM’s full potential (compared to multiple regression analyses). Furthermore, in sampling, researchers are advised to anticipate the use of holdout samples in order to test their results’ robustness. In analyzing the collected data, we encourage authors to improve the evaluation of the results and/or the reporting of evaluation criteria, as a matter of urgency. Formative measurement model evaluation, in particular, requires improvement, but the more common reflective measurements will also benefit from referral to the outlined assessment standards. Finally, the reporting of the inner model’s quality can be increased in terms of the reporting of effect sizes. The above recommendations are valid for both explanatory and exploratory research; however, in exploratory research designs, following the guidelines outlined is even more important, so that we can truly advance theory building based on empirical data.

Finally, advances in PLS-SEM, for instance, corrections introduced by Bentler and Huang (2014) as well as Dijkstra (2014), provide new methods to mimic CB-SEM results. Furthermore, new fit measures for PLS-SEM further support testing and comparing
theories (see Dijkstra and Henseler, 2015a). If these procedures hold what they promise, they will enable researchers to further exploit both the method’s explanatory capabilities for theory testing in combination with its soft-modeling benefits: For instance, complex hierarchical component or second-order models (e.g. Kuppelwieser and Sarstedt, 2014a, b) can be compared to the related models that only include the lower order components or relationships. Hence, if these approaches hold what they promise, PLS-SEM will be capable of delivering results comparable to CB-SEM while keeping most of its advantageous features discussed throughout this paper (Sarstedt et al., 2014a, b).

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