Journal of Purchasing & Supply Management 21 (2015) 259–272

Contents lists available at ScienceDirect

Journal of Purchasing & Supply Management

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

A structured review of partial least squares in supply chain management research

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ARTICLE INFO

Article history:
Received 10 June 2014
Received in revised form
21 March 2015
Accepted 22 April 2015
Available online 12 June 2015

Keywords:
Partial least squares
Structural equation modeling
Supply chain management

ABSTRACT

The application of structural equation modeling (SEM) in the supply chain management (SCM) context has experienced increasing popularity in recent years. Although most researchers are well equipped with a basic understanding of the traditional covariance-based SEM (CBSEM) techniques, they are less familiar with the appropriate use of partial least squares (PLS) SEM. To fill this gap, the current paper critically reviews the use of PLS in 75 articles published in leading SCM journals from 2002 until 2013. The review indicates the potential of PLS, but also its limitations. A comparison across PLS reviews from various disciplines suggests that SCM research applies the same or even higher reporting standards in performing a PLS analysis and reporting the results than other disciplines (e.g., marketing or strategic management) that use PLS. However, SCM researchers often do not fully exploit the method's capabilities, and sometimes they even misapply it. This review thus offers guidelines for the appropriate application of PLS for future SCM research.

1. Introduction

Structural equation modeling (SEM) has become the norm for analyzing the cause–effect relations between latent constructs (Hair et al., 2011). SEM techniques can be divided into two general families: covariance-based techniques and variance-based techniques (Henseler et al., 2009). Researchers have so far concentrated primarily on covariance-based SEM (CBSEM) techniques (Medsker et al., 1994; Shook et al., 2004; Steenkamp and Baumgartner, 2000). However, one variance-based technique – partial least squares (PLS) – has gained in popularity, and various disciplines, including supply chain management (SCM) (Hartmann and De Grahl, 2011), marketing (O'Cass and Weerawardena, 2010), and management information systems (Furneaux and Wade, 2011), have increasingly used PLS in recent years because violations of some of the key assumptions of CBSEM limit its applicability. For example, the steady growth of the use of PLS can be attributed to the claim that the approach can estimate research models using small samples and can model both reflective and formative constructs (Peng and Lai, 2012). The application of PLS, however, is controversial: its opponents state that PLS is less rigorous than CBSEM and ineffective for testing theory (Rönkkö and Evermann, 2013).

The growing number of articles published using PLS in SCM (e.g., Caniëls et al., 2013; Hartmann and de Grahl, 2012; Thornton et al., 2013) and the controversy regarding the application of PLS in various disciplines (e.g., Hair et al., 2011; Henseler et al., 2014; Rigdon, 2012; Rönkkö, 2014; Rönkkö and Evermann, 2013) suggest the need to compare and contrast how PLS is being used in the SCM literature. Thus, a structured review that is targeted directly at SCM research – one that includes the pros and cons of applying PLS – seems warranted. The discipline also faces particular challenges, such as less developed empirical research and increasing difficulties in collecting large samples (De Beuckelaer and Wagner, 2012; Peng and Lai, 2012), that enhances the value of such a review at this time.

Guidelines and minimum reporting standards are crucial for advancing research (Ringle et al., 2012b); they not only help authors to develop and execute their own studies, but also help in evaluating the work of others (Gefen et al., 2011). The importance of guidelines for the use of PLS has already been recognized in other fields, including marketing, IT management and accounting, strategic management, and operations management (Hair et al., 2012a; Henseler et al., 2009; Hulland, 1999; Lee et al., 2011; Peng and Lai, 2012; Ringle et al., 2012b). Users of the PLS method can benefit from its use only if they fully understand the underlying principles, apply it correctly, and report the results properly (Hair et al., 2012c). The objective of this study, therefore, is to provide a comprehensive, detailed, and organized overview of the use of PLS in SCM. Specifically, we investigate 75 applications of PLS that were published in ten major SCM journals from 2002 to 2013.

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http://dx.doi.org/10.1016/j.pursup.2015.04.005
1478-4092/

Following Hair et al. (2012a), we comment on our findings and provide researchers and reviewers in our field with guidelines they can use as a checklist for effectively applying PLS and interpreting its results. Thus, this paper contributes to a more balanced and informed application of PLS in SCM.

The remainder of the article is structured as follows: in the next section we give a concise overview of PLS and describe its working principles. In section three, we address PLS in the context of SCM research and present the findings from our extensive literature review. We weave into these findings our recommendations on how to evaluate and use PLS in the context of SCM research. Finally, section four sums up the key findings and draws a conclusion.

2. Overview of PLS

Originally developed under the name nonlinear iterative partial least squares (NIPALS) by Wold in the 1960s (Wold, 1966) and extended by Lohmöller a few decades later (Lohmöller, 1989), PLS was designed as an alternative to CBSEM for modeling complex multivariate relationships among observed and latent variables (Esposito Vinzi et al., 2010). It gained popularity with the publications of Fornell and Bookstein (1982) and Chin (1998) and has been used frequently across disciplines ever since.

A PLS path model consists of two components: a measurement model and a structural model (Henseler et al., 2009). The measurement model, also called an outer model, shows the unidirectional predictive relationships between each latent construct and its associated observed indicator variables. Indicator variables are always associated with a single latent construct. PLS distinguishes between two different measurement models: reflective and formative ones. Reflective indicators are seen as functions of the latent construct, meaning that changes in the latent construct lead to changes in the indicator variables. Formative indicators, in contrast, cause a latent construct, and changes in the indicator variables are visible in the changes in the latent construct (Hair et al., 2011). The structural model, also called the inner model, reflects the relationships that exist between the unobserved or latent constructs. In the structural model, differentiation arises between exogenous and endogenous constructs. Exogenous constructs do not have any structural path relationships pointing at them, thus, they are not caused by any other construct in the model. Endogenous constructs have at least one structural path relationship pointing at them, thus, they are caused by at least one construct in the model (Hair et al., 2011).

The basic PLS algorithm includes three stages (Henseler et al., 2009). Stage 1 consists of the iterative estimation of latent variable scores. In this stage, a four-step iterative process is repeated until convergence is obtained:

1. The outer proxies of the latent construct scores are computed as linear combinations of the values of all (standardized) indicators associated with a particular latent construct.
2. The PLS algorithm computes proxies for the structural model relationships.
3. The inner proxies of the latent construct scores are calculated as linear combinations of the outer proxies' respective adjacent latent constructs using the previously determined inner weights.
4. The outer weights are calculated. The approach for this calculation differs based on the type of measurement model each construct represents: When a construct is measured reflectively, the outer weights are calculated as the correlations between the inner proxy of each latent construct and its indicator variables. When a construct is measured formatively, the outer weights result from the ordinary least squares regression of the inner proxy of each latent variable on its indicators (Hair et al., 2011).

These four steps are repeated until the sum of the change in outer weights between two iterations has decreased to a predefined limit. The recommended limit is a threshold value of 10^{-5} to ensure the convergence of the PLS algorithm. The algorithm ends after Stage 1, delivering latent variable scores for all latent variables. Stage 2 then comprises the estimations both of outer weights/loading and of path coefficients. The final stage, Stage 3, consists of the estimation of the mean and the location parameters (i.e., OLS intercepts) for the indicators and latent variables in the model (Henseler et al., 2009; Lee et al., 2011).

PLS is aimed at maximizing the explained variance of the dependent latent constructs by estimating partial model relationships using composites in an iterative sequence of ordinary least squares regressions (Hair et al., 2011). Meanwhile, CBSEM's objective is to reproduce the theoretical covariance matrix, without focusing on explained variance (Hair et al., 2011). Latent variables in PLS, unlike in CBSEM, are estimated as exact linear combinations of their indicators and are therefore not true latent variables as they are defined in SEM (Marcoulides et al., 2009).

CBSEM requires that a set of assumptions or conventions be fulfilled, including, for example, the multivariate normality of data and the minimum sample size (Hair et al., 2011). The use of PLS is advocated if these assumptions cannot be maintained because, as some researchers have argued, PLS has minimal requirements on sample size and data characteristics (Hair et al., 2011; Peng and Lai, 2012). Furthermore, while the inclusion of formative and reflective indicators in CBSEMs might cause identification problems, PLS is well suited for both formative and reflective indicators (Henseler et al., 2009). In addition, PLS can be used to estimate highly complex models. In more complex models, the number of latent and observed variables might be high, compared to the number of observations (Henseler et al., 2009). Moreover, some researchers argue that PLS is more suitable for prediction and theory development, while CBSEM is more appropriate for theory testing and confirmation (Hair et al., 2011).

PLS thus has been the subject of much debate. One half of the research community argues that PLS has its advantages when it is correctly used, and might even be a "silver bullet" (Hair et al., 2011); the other half is strictly against its use, arguing that it is inferior to traditional CBSEM techniques (Antonakis et al., 2010; Rönkkö, 2014; Rönkkö and Evermann, 2013). Researchers opposing the use of PLS criticize the bias and inconsistency of parameter estimates, its inability to model measurement errors, and the lack of an over-identification test, which would allow for testing a model causally (Hwang et al., 2010; Peng and Lai, 2012; Rönkkö and Evermann, 2013). In their recent article about commonly held but wrong beliefs about PLS, Rönkkö and Evermann (2013) state that most of the common beliefs about PLS are not based on statistical theory or simulation studies but on previously published articles, which show no proofs for the claims made. Commenting on Rönkkö and Evermann's (2013) article, Henseler et al. (2014) argue that these claims about PLS in turn, are not justified and that PLS does offer advantages for exploratory research. McIntosh et al. (2014) take stock of the two articles, contending that PLS should divorce itself from the factor-analytic tradition and focus on developing itself further as a purely composite-based statistical methodology. The composite factor model differs from the common factor model by relaxing the strong assumption that all the covariation between a block of indicators is explained by a common factor. Thus, the composite factor model does not impose any restrictions on the covariances between indicators of the same construct. Rather, composites are formed as linear combinations of