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Partial least squares path modeling: Quo vadis?

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1 Introduction

Partial least squares (PLS) path modeling is a multivariate statistical technique that relies on an alternating least squares algorithm as invented by Wold (1974). It is regarded as the "most fully developed and general system" (McDonald 1996, p. 240) among variance-based estimators for structural equation modeling, and it is applied across a wide range of disciplines, including information systems research (Marcoulides and Saunders 2006) and marketing (Hair et al. 2012). In its most modern appearance, it can be regarded as a structural equation modeling (SEM) technique that can handle various forms of construct operationalizations, including reflective measurement and composite models (for a distinction, see Rigdon 2012; Henseler 2017).

In recent years, the use of PLS has been the subject of fierce debate between proponents and opponents. Whereas some researchers strongly advocate the use of PLS and call it a "silver bullet" (Hair et al. 2011), others believe PLS should not be used at all (Antonakis et al. 2010). For researchers who promulgate, extend, or apply PLS, the debate has been fruitful because it has helped to identify several weaknesses of PLS, for example, the inconsistency of parameters in the case of reflective measurement models, the lack of goodness-of-fit measures, and the low sensitivity of the Fornell-Larcker criterion to detect problems with regard to discriminant validity (Rönkkö and Evermann 2013). Subsequently, many new developments have led to substantial improvement and enrichment of PLS, including a correction for attenuation if constructs are modeled as common factors (consistent PLS, see Dijkstra and Henseler 2015b), a new criterion to assess the

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discriminant validity called the heterotrait-monotrait ratio of correlations (HTMT, Henseler et al. 2015), the standardized root mean square residual (SRMR) as an approximate measure of fit (Henseler et al. 2014), bootstrap-based tests of overall model fit (Dijkstra and Henseler 2015a), a new approach for estimating and testing second-order constructs (van Riel et al. 2017), a clarification on which auxiliary theories PLS can actually model (Henseler 2017), and updated guidelines for model specification and reporting (Henseler et al. 2016).

In the past, many papers focused on the question of ‘why should researchers use PLS?’. Typical answers referred to the alleged advantages of PLS, such as the ability to handle both formative and reflective measurements, low sample size requirements, and a lack of distributional assumptions (c.f. Henseler et al. 2009). Unfortunately, the situation is not that simple, and the generality of these characteristics is limited. Methodologists currently appear to refrain from making claims about PLS at all (Rigdon et al. 2017) or ask for future research to identify advantages of PLS (Rigdon 2016). At the moment, the question about the reasons to use PLS remains unanswered. This conclusion is less dramatic for PLS than it might appear on first sight. Actually, the discussion of why to use PLS could benefit from a slight reformulation of the question, replacing the “why?” by “for which purpose?”. PLS is nothing but a tool, and tools should be assessed in relation to the task that they are meant to accomplish (Goodhue and Thompson 1995).

2 For which purpose should one use PLS?

Empirical research in business and social science comes in many varieties. The dominant types of research are confirmatory, explanatory, exploratory, descriptive, and predictive. PLS can be of value for all of these types of research.

Confirmatory research aims to understand the causal relationships between variables. In the special case of structural equation modeling, analysts are interested in the causal relationships between theoretical concepts. Typically, researchers formulate a theory such that some effects or relationships are hypothesized to have a fixed value, most often zero. In that way, they obtain degrees of freedom (one per fixation/constraint) and make their theory accessible to empirical testing. In the measurement model, this can mean that the axiom of local independence holds, which entails that the correlations among indicators of a common factor can be fully attributed to the existence of an underlying latent variable (Lazarsfeld and Henry 1968). In the structural model, researchers may look for mediation, which means that a certain variable has only an indirect effect on another variable, and the direct effect is zero (Nitzl et al. 2016). Confirmatory research requires a test of global goodness of model fit based on the discrepancy between the empirical and the model-implied variance-covariance matrix. Only since the advent of global goodness of fit tests (Dijkstra and Henseler 2015a; Henseler et al. 2014) can PLS be employed for confirmatory research.

Explanatory research also aims to understand the causal relationships between variables; both confirmatory and explanatory research are sometimes referred to as causal research. As in the case of confirmatory research, analysts wish to obtain consistent estimates of the relationships among constructs. The distinguishing aspect of explanatory research is that analysts are interested in explaining a specific phenomenon that is treated as a dependent variable. Consequently, the structural equation models used for explanatory research typically consist of one endogenous and one or more exogenous constructs. Since structural models of this type are saturated (i.e., they have zero degrees of freedom), the structural model is not assessable in terms of goodness of fit but only in terms of strength of fit (Henseler and Sarstedt 2013), i.e., the R-squared value of the endogenous construct. Nevertheless, in explanatory research, the measurement models of multi-item constructs can and should be tested for goodness of fit. Thus, explanatory research using PLS relies to some extent on confirmatory research to test the auxiliary theory. If an analyst finds it difficult to distinguish between confirmatory and explanatory research, the following heuristic may help: If analysts have a eureka experience because they find empirical support for a model that tries to explain a part of the world without a specific effect or relationship, they are most likely conducting confirmatory research. If the empirical support of an effect creates a eureka experience, then the analysts are most likely conducting explanatory research.

Exploratory research aims to pinpoint possible relationships between constructs and can best be understood as a heuristic for theory building. As such, it is an inductive way of reasoning. Herman Wold, the inventor of PLS, regarded model building as the core task of PLS (Wold 1989). In his view, a researcher should design an exploratory structural equation model "on the joint basis of his rudimentary theoretical knowledge, his experience and intuition about the problems explored, and the data that are at his disposal" (Wold 1980, p. 70). PLS path models are developed "in dialogue with the computer" (Wold 1985, p. 240). For analysts, it can be tempting to continuously adapt a structural equation model to the data at hand and then report hypothesis tests of the model fit and parameter estimates. Adapting a model to the data implies that the model itself becomes a random variable; consequently, any hypothesis test of a presumably fixed model will provide misleading results. Researchers using PLS for exploratory research should regard PLS at that stage as a tool for theory building not theory testing. In analogy to other exploratory research techniques, such as cluster analysis or qualitative research, PLS should be considered an atheoretical technique as long as it is used for exploratory research. Since exploratory research tends to probe for possible explanations and hypotheses, analysts strive for high sensitivity and are willing to compromise specificity. In this situation, the somewhat higher sensitivity of PLS (Reinartz et al. 2009) is beneficial. To ensure specificity, exploratory research should be followed by causal research.

Descriptive research is mainly interested in quantities that describe a population. The dominant applications are national customer satisfaction indices, such as the Swedish Customer Satisfaction Index (Fornell 1992), the American Customer Satisfaction Index (Fornell et al. 1996), and the European Customer Satisfaction Index (Tenenhaus et al. 2005). However, customer satisfaction is not the only application of indices. Researchers have created a plethora of other indices, for instance, the Air Force Warehouse Logistics Index (Sohn et al. 2007), the Global Competitiveness Index (Petrarca and Terzi forthcoming), the Respondent Burden Index (Fricker et al. 2012), and the Technology Commercialization Success Index (Sohn and Moon 2003). Descriptive research using PLS also encompasses a prescriptive element. In particular, the PLS algorithm provides a prescription for dimension reduction (Dijkstra and Henseler 2011) i.e., it prescribes how variable values should be aggregated to proxy scores.

Predictive research aims to make predictions for individual cases. It differs from causal and descriptive research in two important ways (Shmueli et al. 2016). First, whereas causal and descriptive research attempt to explain or describe the data at hand, predictive research focuses on providing a prognosis for new data. Second, whereas causal and descriptive research make aggregate statements such as effects and average levels, predictive research makes individual statements for each case. PLS is well suited for prediction purposes.

Wold (Wold 1982) emphasized the "causal-predictive" nature of the structural paths, and a recent special issue of the Journal of Business Research was dedicated to "PLS and prediction" (Cepeda Carrión et al. 2016). While there are other statistical techniques that outperform PLS with regard to prediction capability, PLS is transparent about how the prediction is produced. Thus, in contrast to many other techniques, PLS is not a black box. As Shmueli et al (2016, p. 4552) stated, PLS "aims to maintain interpretability while engaging in predictive modeling."

In practice, the distinction between the five aforementioned types of research is not always that clear-cut. Combinations of research types are common, e.g., making predictions based on an explanatory model. Nevertheless, distinguishing between the five types of research can help to identify certain purposes for which PLS is an adequate statistical tool. For each type of research, one can identify situations in which PLS can be of value for an analyst. These are expressed in the form of the following five propositions:

1. PLS is a suitable technique for confirmatory purposes if a structural equation model contains one or more constructs operationalized as a composite. The analyst's focus will predominantly lie on the model's goodness of fit.
2. PLS is a suitable technique for explanatory purposes if a structural equation model contains one or more constructs operationalized as a composite. The analyst's focus will predominantly lie on the endogenous variables' R-squared, the statistical inference of path coefficients, and effect sizes.
3. PLS is a suitable technique for exploratory purposes if researchers are searching for a quick, graphic-supported indication of whether there might be a relation between two proxies. The analyst's focus will predominantly lie on the path coefficients.
4. PLS is a suitable technique for predictive purposes if the analyst is also interested in understanding how the prediction is made. The analyst's focus will predominantly lie on the prediction errors of the model and the predictive relevance of each effect.
5. PLS is a suitable technique for descriptive purposes if the weights of a focal index take into account the nomological net. The analyst's focus will predominantly lie on the (average) proxy scores and the proxy weights.

Finally, PLS can be used for auxiliary purposes. In such situations, PLS is not directly applied to answer a research question but as a preparatory analytical step within a more extensive analytical design. Researchers predominantly apply PLS to obtain construct scores or inter-construct correlations that can be used in follow-up analyses. For instance, Benitez et al. (2018) use covariance-based structural equation modeling to estimate a non-recursive structural model using an inter-construct correlation matrix obtained through PLS. PLS construct scores play a pivotal role in two-step procedures for estimating moderating effects (see, e.g., Dijkstra and Schermelleh-Engel 2014; Fassott et al. 2016; Henseler and Fassott 2010), non-linear effects (see, e.g., Henseler et al. 2012), and higher-order constructs (see, e.g., van Riel et al. 2017). Moreover, they form the basis for various segmentation approaches (see, e.g., Sarstedt and Ringle 2010). PLS can also serve as an emulator of canonical correlation analysis (Wold 1966) and various generalizations thereof (Tenenhaus and Esposito Vinzi 2005).

As Fig. 1 illustrates, PLS is at a crossroads. Awareness about the concrete purpose for which one wants to use PLS is not only important for analysts seeking their way but also for methodologists who are dedicated to improving and enhancing PLS. Whenever they are strengthening the method, they should ask themselves which type of research question they help PLS answer. By devoting research efforts to certain aspects of PLS, methodologists can have a substantial impact on when and how intensively PLS will be used in the future.

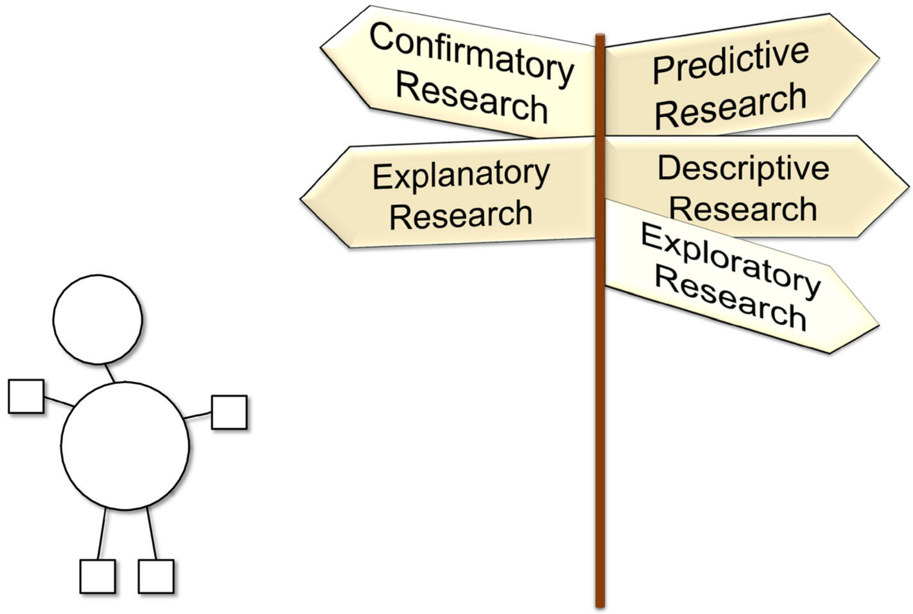

Fig. 1 PLS, quo vadis?

3 The papers of the special issue

This special issue contains four papers that extend or apply PLS. They cover a wide spectrum with regard to the type of research. The four papers all provide a unique contribution to the further development and application of PLS.

The article "Partial least squares path modeling using ordinal categorical indicators" by Schuberth et al. departs from the notion that researchers would sometimes like to apply PLS but face the problem that their data is not metric but ordinal. This can occur in questionnaire-based research if scales with too few options were selected. As a solution, the authors introduce ordinal consistent partial least squares (OrdPLSc), a new consistent variance-based estimator that makes use of polychoric correlations. OrdPLSc enables estimation of the structural equation models of composites and common factors if some or all indicators are measured on an ordinal categorical scale. A Monte Carlo simulation validates the efficacy of the new method and confirms that OrdPLSc provides almost unbiased estimates. If all constructs are modeled as common factors, OrdPLSc's estimates are close to those obtained from mean- and variance-adjusted weighted least squares (WLSMV). OrdPLSc is most helpful for models that contain common factors as well as composites. As can be derived from the quest for consistent and unbiased estimates, Schuberth et al. are mainly concerned with confirmatory and explanatory research.

In their article titled "What matters most: importance-performance matrix analysis of the factors influencing international postgraduate students psychological and sociocultural adaptations," Shafaei and Razak present the design and outcomes of an empirical study explaining a relevant phenomenon of international higher education, namely, cross-cultural adaptation. Based on their sample of international postgraduate students from major research universities in Malaysia, the authors conclude that perceived stereotype images and adjustment attitude affect the psychological and sociocultural adaptations of students in Malaysia, whereas attachment attitude does not have an influence. English language proficiency is not related to psychological adaptation. The use of importance-performance matrix analysis underlines the combined application of explanatory and descriptive research.

In contrast to the previous paper, the article written by Rodríguez-Entrena et al. titled "Assessing statistical differences between parameter estimates in Partial Least Squares path modeling" does not provide an immediate answer to the question "What matters most?". Instead, it provides a technique that helps researchers to study research questions of this type in general. Concretely, it introduces bootstrap-based confidence intervals to statistically assess differences among structural model parameters using PLS. The authors illustrate the applicability of their approach with the example of an established information systems theory (technology acceptance model) to assess whether two parameter estimates derived from the same sample are statistically different. Business success factor research in particular can benefit from this approach because it enables discrimination of effective management instruments from less effective ones.

The paper by Schreier et al. titled "Question order effects in partial least squares path modelling: an empirical investigation" studies how a particular factor of research design impacts the results of PLS analyses. The paper focuses on question order effects that may be found in product or service quality studies—a typical domain of PLS path modeling. A central finding is that when there are questions about details as well as overall questions, it does matter in which order they are asked. The implications of this paper are particularly valuable during the design phase of an empirical study.

I would like to thank the editor of Quality & Quantity, Vittorio Capecchi, for providing the opportunity to publish this special issue. Moreover, I would like to express my gratitude to the editorial assistant Massimiliano Geraci and Springer's production editor Ambiga Selvaraj for all their support in preparing the special issue. Special thanks goes to the reviewers, who did an excellent job in guiding the authors. Finally, I wish that the four papers are well received by the academic community.

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