# Prediction-oriented modeling in business research

# by means of PLS path-modeling

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# Prediction-oriented modeling in business research by means of PLS path-modeling

**Abstract**

Under the main theme "prediction-oriented modeling in business research by means of partial least squares path modeling" (PLS), the special issue presents 17 papers. Most contributions include content from presentations at the 2nd International Symposium on Partial Least Squares Path Modeling: The Conference for PLS Users, which took place at the Universidad de Sevilla (Spain) from June 16 to 19, 2015. This conference provided PLS users with a platform for the fruitful exchange of ideas on variance-based structural equation modeling. At the same time, the conference addressed the latest methodological advances and their use in research practice. Finally, the conference resumed and enriched the ongoing discussion on the strengths and weaknesses of PLS.

Researchers often emphasize that predictive capabilities is a strength of the PLS method. Nevertheless, methodological advances and applications in this direction are rare. The scientific committee therefore selected high-quality papers that mainly advance PLS and prediction. The special issue editors believe this special issues will become the starting point for a more intensive use of predictive modeling in the social sciences discipline and for additional advances that will exploit PLS' capabilities in this area.

Keywords: Partial least squares; prediction-oriented modeling; business research; quantitative methods

**Prediction-oriented modeling in business research**

**by means of partial least squares path modeling**

## 1. Introduction

Partial least squares path modeling (PLS; Chin, 1998; Dijkstra, 2010; Lohmöller, 1989; Wold, 1982) is a variance-based method to estimate composite-based path models (Hair, Hult, Ringle, & Sarstedt, 2017; Henseler, Dijkstra, Sarstedt, Ringle, Diamantopoulos, Straub, Ketchen, Hair, Hult, & Calantone, 2014). As numerous review studies show, PLS enjoys rapidly increasing usage in various business disciplines, such as accounting (Lee, Petter, Fayard, & Robinson, 2011), family business (Sarstedt, Ringle, Smith, Reams, & Hair, 2014b), management information systems (Ringle, Sarstedt, & Straub, 2012), marketing (Hair, Sarstedt, Ringle, & Mena, 2012b), operations management (Peng & Lai, 2012), strategic management (Hair, Sarstedt, Pieper, & Ringle, 2012a), and tourism (do Valle & Assaker, 2015). Even though the popularity of PLS continues to increase, researchers often call for more rigor when applying the method (e.g., Hair, Ringle, & Sarstedt, 2013; Rigdon, Becker, Rai, Ringle, Diamantopoulos, Karahanna, Straub, & Dijkstra, 2014; Roldán & Sánchez-Franco, 2012; Sarstedt, Ringle, Henseler, & Hair, 2014a). At the same time, in the context of PLS, Rigdon (2014, p. 166) notes: “We have seen a long period where our choice of statistical tools has shaped our research goals, exalting parameter estimation and fit assessment and neglecting prediction. In the future, we need to have our choice of goals shaping our tools.” However, new PLS developments primarily address the method’s explanatory and confirmatory capabilities so far. Advances of the PLS include consistent PLS estimates for factor models (Dijkstra & Henseler, 2015b), the confirmatory tetrad analysis for testing the kind of measurement model and construct (Gudergan, Ringle, Wende, & Will, 2008), the heterotrait-monotrait ratio of correlations (HTMT) for assessing discriminant validity (Henseler, Ringle, & Sarstedt, 2015), methods for uncovering unobserved heterogeneity (e.g., Becker, Rai, Ringle, & Völckner, 2013; Ringle, Sarstedt, & Schlittgen, 2014), different multigroup analysis approaches (Chin & Dibbern, 2010; Sarstedt, Henseler, & Ringle, 2011), testing measurement invariance of composites (Henseler, Ringle, & Sarstedt, 2016), as well as the use of PLS for non-recursive models and overall goodness-of-fit measures (Dijkstra & Henseler, 2015a). All these changes culminate in revised guidelines for PLS' confirmatory research use (Henseler, Hubona, & Ray, 2016), as well as updated primers and new advanced PLS textbooks (Hair et al., 2017; Hair, Sarstedt, Ringle, & Gudergan, 2018).

While PLS researchers concentrate their efforts largely on confirmatory research, PLS' use for predictive research problems is somewhat out of focus. Yet researchers often emphasize its predictive capabilities as a strength of the PLS method (e.g., Hair, Ringle, & Sarstedt, 2011). At the moment, methodological advances and applications in this direction are rare. Against this background, the "2nd International Symposium on Partial Least Squares Path Modeling: The Conference for PLS Users" worked with the Journal of Business Research (JBR) to develop a special issue that includes advances in PLS and prediction, as well as substantial PLS applications in marketing and management research that mainly have an orientation towards prediction. The purpose of the special issue is to establish a starting point for the more intensive use of predictive modeling in the social sciences discipline and to initiate additional advances to exploit PLS' capabilities in this area. Most papers included in the special issue are extended versions of papers presented at the 2nd International Symposium on Partial Least Squares Path Modeling: The Conference for PLS Users.

## 2. The 2nd International Symposium on PLS: The Conference for PLS Users

From June 16 to 19, 2015, the Universidad de Sevilla, Spain, hosted the conference for PLS users. Gabriel Cepeda Carrión (University of Seville), Jörg Henseler (University of Twente and Universidade Nova de Lisboa), Christian M. Ringle (Hamburg University of

Technology, TUHH, and The University of Newcastle), and José Luis Roldán (University of Seville) chaired the conference. The International Symposium on PLS was an ideal place to answer the challenges pertaining to advanced issues in PLS, such as its orientation towards prediction. The conference gathered scholars from more than 30 countries, who presented their contributions and obtained rich feedback from the participants. Given the tradition of the Department of Business Administration and Marketing at the Universidad de Sevilla regarding the application and diffusion of the PLS technique, the University was a perfect venue for this PLS meeting.

The scientific program committee handled more than 80 submissions and decided on the final conference program; this committee comprised the following members: Francisco J. Acedo (Universidad de Sevilla), Sönke Albers (Kühne Logistics University), Tomàs Aluja (Universitat Politècnica de Catalunya, Spain), Nicholas J. Ashill (American University of Sharjah), Jan-Michael Becker (University of Cologne), Diogenes Bido (Universidade Presbiteriana Mackenzie), Pedro Simoes Coelho (Universidade Nova de Lisboa), Tim Coltman (University of Wollongong), Timothy Devinney (The Universtiy of Leeds), Theo Dijkstra (University of Groningen), Andreas Eggert (University of Paderborn), Vincenzo Esposito Vinzi (ESSEC), John Ettlie (Rochester Institute of Technology), Siegfried Gudergan (The University of Newcastle), Michael Haenlein (ESCP, France), Joe Hair (Kennesaw State University, U.S.A.), Andrew Hardin (University of Nevada), Geoffrey Hubona (Virginia Commonwealth University), John Hulland (University of Georgia), Tomas Hult (Michigan State University), Izani Ibrahim (University Kebangsaan Malaysia), Surinder Kahai (Binghamton University, State University of New York), Byron Keating (University of Canberra), George Marcoulides (University of California, Santa Barbara), David Midgley (INSEAD), Yuichi Mori (Okayama University), Aron O'Cass (University of Tasmania), Shintaro Okazaki (Universidad Autónoma de Madrid), David Xiaosong Peng (University of

Houston), Arun Rai (Georgia State University), Thurasamy Ramayah (University Sains Malaysia), Edward E. Rigdon (Georgia State University), James Robins (Vienna University of Economics and Business), Gastón Sánchez (University of California, Berkeley), Marko Sarstedt (Otto-von-Guericke-University Magdeburg), Holger Schiele (University of Twente), Rainer Schlittgen (University of Hamburg), Judit Simon (Corvinus University of Budapest), Rudolf Sinkovics (Manchester Business School), Detmar Straub (Georgia State University), Dirk Temme (University of Wuppertal), Michel Tenenhaus (HEC), Jason Bennett Thatcher (Clemson University), Ron Thompson (Wake Forest University), Sunil Venaik (The University of Queensland), and Martin Wetzels (Maastricht University).

Many of the conference papers and sessions offered important developments in PLS' path modeling use. The conference primarily increased the applicability of PLS in the management and marketing field. Most of the sessions were truly unmissable. The plenary sessions had noteworthy keynote speakers in the PLS field, such as Edward E. Rigdon (Georgia State University), Theo K. Dijkstra (University of Groningen), Joseph F. Hair (Kennesaw State University), and Wynne W. Chin (University of Houston). The following videos of the conference's key moments are available:

- Conference opening: http://tv.us.es/videoembed/?numberpost=30259
- Keynote talk I: Reconciling composite-based and factor-based approaches to structural equation modeling (Edward E. Rigdon): http://tv.us.es/videoembed/?numberpost=30263
- Keynote talk II: PLS & CB SEM: A weary and a fresh look at presumed antagonists (Theo K. Dijkstra): http://tv.us.es/videoembed/?numberpost=30269
- Keynote talk III: On partial least squares' variance-based component SEM (VBSEM) versus covariance-based SEM (CBSEM) for confirmatory analysis: It's all about the

components and variance explained (Wynne W. Chin): http://tv.us.es/videoembed/?numberpost=30273

- Featured talk: Confirmatory composite analysis (Jörg Henseler): http://tv.us.es/videoembed/?numberpost=30277
- Panel session: The future of PLS (Discussants: Edward E. Rigdon, Theo K. Dijkstra, Galit Shmueli. Moderator: Jörg Henseler): http://tv.us.es/videoembed/?numberpost=30281

Several sessions, and specifically the panel session, were devoted to this special issue's topic: the prediction-oriented nature of PLS.

## 3. PLS and its prediction-oriented results assessment

Researchers and practitioners appreciate PLS' various advantageous features for practical applications (e.g., Hair et al., 2012b). Orientation towards prediction has been one of PLS' key building blocks since its creation (Jöreskog & Wold, 1982; Wold, 1985). Recent conceptual (Chin, 2010a; Sarstedt et al., 2014a) and empirical studies (Becker, Rai, & Rigdon, 2013; Evermann & Tate, 2012) substantiate the suitability of PLS path modeling for predictive purposes. However, when researchers come to assessing the predictive capabilities of PLS, the Stone-Geisser $Q^2$ criterion (Geisser, 1974; Stone, 1974) and the $q^2$ predictive effect size, which the blindfolding routine deliver (e.g., Hair et al., 2017), are the only standard evaluation criteria thus far (Chin, 1998, 2010b).

The special issue thus aims at providing methodological advances in PLS prediction and management and marketing applications that address this issue. The JBR editor-in-chief, Arch Woodside, the special issue editors, and the reviewers focus on the use of established predictive validity assessment. In addition, they suggest the use of holdout samples in PLS, as

Hair et al. (2012b) call for, and the use of fuzzy-set qualitative comparative analysis (fsQCA) to test for causal asymmetry (Gigerenzer & Brighton, 2009; Woodside, 2013).

### *3.1. Assessing the Predictive Validity of PLS Path Models Using Holdout Samples*

There are strong recommendations for using cross-validation by means of holdout samples as a standard results assessment routine in PLS (Hair et al., 2012b). The holdout sample assessment allows for determining how well a predictive model will perform in practice, especially when the analysis follows prediction-oriented goals (Ebbes, Papies, & van Heerde, 2011). The use of holdout samples can encourage analysts to find a balance between model fit and prediction capability (Schorfheide & Wolpin, 2012). However, researchers rarely use holdout samples when evaluating their PLS results. Possible reasons for this may be the scarcity of guidelines on the use of holdout samples in the PLS context resulting in a lack of analysts' knowledge about conducting holdout sample assessments, or the lack of holdout sample implementation in leading PLS software packages.

As a point of departure for the more frequent use of holdout samples, the guest editors present an eight-step PLS procedure (Figure 1 and Figure 2). To begin with (Step 1), randomly divide your sample into a training sample (comprising more than half of the data, e.g. see Steckel & Vanhonacker, 1993) and a holdout sample (the remaining observations). Then create two data sets from your original set of data. Next, in Step 2, estimate the PLS path model parameters, using the training sample, and save the results. In Step 3, standardize the holdout sample data (i.e., subtract the mean of each indicator of the holdout sample and divide each mean by its standard deviation). Alternatively, leading PLS software applications provide a standardized data matrix in their results report. Thereafter, create construct scores for the holdout sample as linear combinations of the respective indicators and the weights obtained from the training sample (Step 4). Next, standardize the construct scores of the holdout sample (mean value subtraction and standard deviation division; Step 5).

Figure 1 here.

In Step 6, create prediction scores for each endogenous construct as a linear combination of the exogenous constructs (using the scores obtained from Step 4) and the path coefficients from the training data model estimation. Now, determine the $R^2$ value (Step 7). Calculate the proportion of explained variance ($R^2$) as the squared correlation of the prediction scores and the construct scores for each endogenous construct of the holdout sample. Finally, in Step 8, report the $R^2$ values of the holdout sample and compare them with the $R^2$ values obtained in the training sample. Both $R^2$ values should be fairly similar. This kind of cross-validation substantiates how the statistical analysis results will generalize to an independent data set, as well as how well a predictive model will perform in practice.

Figure 2 here.

Researchers can use this step-by-step approach to conduct the cross-validation of their PLS results. They may want to use different statistics, such as the root mean square error (RMSE) or the mean absolute error (MAE, e.g. see Greene, 2011). The guest editors' expectations are that leading PLS software applications will offer the use of holdout samples to conduct cross-validation routines. Thereby, this kind of assessment will become a standard routine for result analysis and reporting.

### *3.2. Testing causal asymmetry*

Woodside (2013) emphasizes the importance of an overview for exploring actual phenomena and the appropriateness of fuzzy-set qualitative comparative analysis (fsQCA; Ragin, 2008, 2009) for analyzing data focuses on a case-level recipe that explains the influence of all the ingredients, rather than the variables' unidirectional net effects. FsQCA is therefore a strong tool for testing causal asymmetry (Fiss, 2011; Marx, Rihoux, & Ragin, 2014; Wagemann, Buche, & Siewert, 2016; Woodside, 2013). A fuzzy set is a middle dichotomy, in which a qualitative narrative determines the extent to which a person belongs (Woodside, 2013). Previous studies use statistical methods to establish causal relations in various models to examine individual factors that affect the outcome of events. A sufficient condition is a variable, or a combination of variables, that could lead to a particular outcome (Ragin, 2008; Woodside, 2013). FsQCA uses a consistency and coverage index to evaluate antecedents and their combinations (Ragin, 2008, 2009). A consistency index is a subset of the relation of antecedent(s) to outcome(s) (Woodside & Zhang, 2013) and assesses the extent to which cause, or a causal combination, accounts for an outcome. Ragin (2008) and Woodside and Zhang (2013) provide more detail on calibrations in fsQCA.

Many authors in this special issue conduct an fsQCA to demonstrate the inexistence of causal asymmetry, thus showing that their results are not subject to causal equifinality or asymmetry (Fiss, 2011; Wagemann et al., 2016). They thus substantiate a correlation-based symmetric analysis of causality when examining and interpreting the estimated PLS path coefficients. The authors use PLS' latent variable scores and the software package fs/QCA 2.5 (Ragin & Davey, 2014), which supports this kind of causal complexity analysis, when conducting the fsQCA (e.g., Woodside, Hsu, & Marshall, 2011; Woodside, Ko, & Huan, 2012). Another way of testing causal asymmetry is to analyze the heteroscedasticity (Hair, Black, Babin, & Anderson, 2010).

**4. Contents of the special issue**

The team of guest editors is pleased to present a comprehensive picture of the different options from which researchers can choose when deciding to adopt PLS as a predictive tool. PLS' orientation towards prediction is by no means a novelty, but by presenting a complete set of papers that discusses the topic, this special issue takes a new approach. The readers find papers ranging from in-depth theoretical and simulation analyses to recent applications of PLS with a predictive orientation. In the following, the guest editors provide a brief overview of the papers in this special issue. These contributions provide researchers with very rich and practical information on how to analyze models with PLS by adopting a prediction focus.

### *4.1. The elephant in the room: Predictive performance of PLS models*

The paper by Galit Shmueli, Soumya Ray, Juan Manuel Velasquez Estrada, and Suneel Babu Chatla is particularly important for this special issue. The authors focus on evaluating PLS models' predictive performance, and how this procedure strengthens theory-building and validation research, as well as making them more relevant for practice. Their contributions are threefold. First, they provide a framework for prediction and predictive evaluation with PLS models. Second, they establish a set of procedures for generating and evaluating predictions from PLS models. Third, they discuss the ways in which the predictive evaluation of PLS models enhance theory building in research and practice.

### *4.2. Assessing the predictive performance of structural equation model estimators*

Joerg Evermann and Mary Tate guide researchers in the choice of appropriate PLS prediction methods. Their study presents two interesting simulation studies that evaluate the performance of different modes and variations of PLS-PM and covariance analysis regarding SEM prediction.

### *4.3. Segmentation of PLS path models by iterative reweighted regression*

Rainer Schlittgen, Christian M. Ringle, Marko Sarstedt, and Jan-Michael Becker introduce a new segmentation approach to variance-based SEM, using partial least squares path modeling (PLS). The iterative reweighted regressions segmentation method for PLS (PLS-IRRS) effectively identifies and treats unobserved heterogeneity in data sets. Compared to existing alternatives, PLS-IRRS is far faster, while delivering results of the same quality. Researchers should therefore routinely use PLS-IRRS to address the critical issue of unobserved heterogeneity in PLS.

### *4.4. Capturing heterogeneity and PLS-SEM prediction ability: Alliance governance and innovation*

Martin Ratzmann, Sigfried Gudergan, and Ricarda Bouncken clarify how PLS and, explicitly, PLS latent interaction effect (PLS-LIE), PLS prediction-oriented segmentation (PLS-POS), and PLS-PATHMOX improve its prediction ability. Based on innovation outcomes produced in cooperative alliances, their study offers significant findings regarding the improvements in the mentioned techniques' prediction ability.

### *4.5. The PLS agent: Predictive modeling with PLS-SEM and agent-based simulation*

Sandra Schubring, Iris Lorscheid, Mathias Meyer, and Christian M. Ringle propose that combining two modeling methods — agent-based simulation (ABS) and PLS-SEM — makes PLS-SEM results dynamic and extend their predictive range. The dynamic ABS modeling method uses a static path model and PLS-SEM results to determine the ABS settings. Besides presenting the conceptual underpinnings of PLS Agent, this research includes an empirical application of the well-known technology acceptance model. In this illustration, the ABS extends the PLS path model's predictive capability from the individual level to the population level by modeling the diffusion process in a consumer network. This study contributes to the recent research stream on predictive modeling by introducing PLS Agent and presenting dynamic PLS-SEM results.

### *4.6. Supplier satisfaction: Explanation and out-of-sample prediction*

Frederick Vos, Holger Schiele, and Lisa Hüttinger replicate and extend previous empirical research on supplier satisfaction. Their findings indicate that beside growth opportunities and reliability, the profitability of a relationship has a major impact. The practical relevance of these findings is important in terms of applying a new procedure to create cross-validated, out-of-sample point predictions, which indicate the satisfactory prediction of cases outside the modeling sample.

### *4.7. An explanatory and predictive model for organizational agility*

Carmen Felipe, Jose L. Roldán, and Antonio L. Leal-Rodríguez explore organizational agility (OA) further by analyzing the part that information systems capabilities' (ISC) variable plays as an antecedent of OA, and the part of absorptive capacity (AC) as a mediator construct. Furthermore, this study tests the negative moderating role of hierarchy culture (HC) in the AC–OA link. Using partial least squares (PLS) and the PROCESS macro, this work finds evidence of the proposed relations and the existence of a conditional mediating situation generated by HC. In addition, the main model with direct effects (ISC and AC as predictors) achieves an appropriate level of predictive validity regarding the key endogenous construct (OA).

### *4.8. The role of organizational capabilities in achieving superior sustainability performance*

Carsten Gelhard and Stephan von Delft contribute to the debate on the triple bottom line by identifying a set of interrelated organizational capabilities (strategic flexibility, value chain flexibility, customer integration) that helps firms achieve superior sustainability performance. The authors provide evidence from a survey of chemical firms in Germany.

### *4.9. Prediction-oriented PLS path modeling in microfinance research*

Antonio Blanco-Oliver, Ana Irimia-Dieguez, and Nuria Reguera-Alvarado focus on the microfinance sector and predict the financial performance of microfinance institutions (MFIs) by means of their social impact, but also consider the mediating role that the portfolio quality (PQ) of the MFIs plays. Further, they advance the PLS literature from a methodological perspective by implementing a validation procedure (a 10-fold, cross-validation method) to assess the predictive accuracy of the PLS model in the study. To this end, they use the function PLSPM, modified with a cross-validation method of R software package.

### *4.10. From knowledge sharing to firm performance: A predictive model comparison*

Zhinning Wang, Pratyush Sharma, and Jinwei Cao investigate how knowledge sharing (KS) contributes to firm performance (FP) by enhancing innovation and/or intellectual capital (IC), using data collected from Chinese high-technology firms. Specifically, the paper proposes three KS-based alternative models to clarify the mediating roles of innovation and IC components in the KS→FP nomological network. The authors compare these models in terms of in-sample explanatory and out-of-sample predictive powers.

### *4.11. Introducing new products that affect consumer privacy: A mediation model*

Caroline Lancelot-Miltgen, Jörg Henseler, Carsten Gelhard, and Aleš Popovič carry out an empirical study in the context of four pervasive IT innovations involving various privacy issues. The findings are consistent in that privacy concerns have an adverse effect on consumers' intention to accept IT innovation. However, this is purely an indirect effect mediated by trust and risk perceptions. By understanding this mechanism, firms can alleviate the potential downsides of their products and increase the odds of their market success.

### *4.12. IT infrastructure and competitive aggressiveness in explaining and predicting performance*

Aseel Ajamieh, Jose Benitez, Jessica Braojos, and Carsten Gelhard examine the relationships between information technology (IT) infrastructure capability, competitive aggressiveness, green supply chain management, and firm performance. Specifically, this study combines IT infrastructure capability (an IT/internal variable) and industry competitive aggressiveness (an external variable) to predict the development of a green supply chain management capability and firm performance. This study tests the proposed research model by applying the partial least squares (PLS) approach to a survey and to a secondary data set from a sample of 203 large firms in Spain. This research provides a good, practical prediction-oriented application in research on IT and firms' environmental sustainability.

### *4.13. Improving prediction with POS and PLS consistent estimations: An illustration*

Siham Mourad and Pierre Valette-Florence contribute to the marketing field by studying how luxury brand consumers react to counterfeiting. They suggest using a consistent PLS model approach that includes counterfeiting resistance, brand experience, perceived risk, attitude toward the brand, and brand loyalty for the methodology. In addition, using PLS, they perform a prediction-oriented segmentation (POS) that demonstrates the existence of three different groups of people with different reactions toward counterfeiting: (1) resistant and brand attached, (2) non-resistant, and (3) detached. The stability of this segmentation is adequate, as is the causal asymmetry of data.

### *4.14. Testing the predictive power of PLS through cross-validation in banking*

Nuria Reguera-Blanco, Antonio Blanco-Oliver, and David Martin-Ruiz analyze the effects of customers' level of e-banking usage on the relationship quality (satisfaction, trust, and commitment) at a Spanish savings bank. The methodology uses PLS path modeling on a primary dataset obtained through an online survey of almost a thousand customers. The authors also undertake predictive validation testing of the models, using holdout samples and testing for causal asymmetry.

### *4.15. Customer equity and predictive CLV in Spanish telecommunication services*

Jose Ramon Segarra Moliner and Miguel Angel Moliner Tena analyze the multidimensionality of the perceived value, brand, and relationship of productivity models, as well as predicting the economic results. They develop a predictive model by analyzing four competing firms. The study context comprises the customers of Spanish telecommunication firms.

### *4.16. Understanding Chinese tourists' food consumption in the United States*

Kaiyang Wu, Carola Raab, Wen Chang, and Anjala Krishen apply the Theory of Planned Behavior (TPB) and use the PLS-SEM method to evaluate different factors that influence

Chinese tourists' consumption behavior toward local food in the United States. The results of this study show that concerns regarding food safety and table manners could aggravate their attitudes toward consuming unfamiliar local foods. However, communication and the food's sensory appeal are not significant in predicting their attitudes toward local food.

### *4.17. Entrepreneurial orientation in the hotel industry: Multi-group analysis of quality certification*

Felipe Hernandez-Perlines analyzes the impact of entrepreneurial orientation on business performance in the hotel sector. Two research methods: PLS-SEM and fsQCA (25 cases) corroborate the results. This twofold confirmation provides his proposed model with validity and robustness, because fsQCA allows for overcoming the drawbacks of PLS-SEM. Thus, this study makes a twofold contribution: a) An analysis of the impact of entrepreneurial orientation on business performance in the hotel sector and b) evidence that quality certification plays a moderating role in this impact.

## Concluding Remarks and Acknowledgements

Researchers often emphasize predictive capabilities as a strength of the PLS method. However, methodological advances and applications in this direction are rare. Consequently, the scientific committee selected high-quality papers for publication that mainly advance PLS and prediction. The JBR special issue provides a forum for topical issues that demonstrate PLS path modeling's usefulness in management and business applications. A description of the method, its empirical applications, and potential methodological advancements that increase its usefulness for research and practice are specifically emphasized. As such, the special issue aims at two audiences: academics involved in the fields of marketing and management and practitioners, such as consultants. Accordingly, theoretical, methodological, and empirical manuscripts were considered as long as the topic had strong implications for business research and practice. The special issue editors believe that this special issue will be the starting point for a more intensive use of predictive modeling in the social sciences discipline and for additional advances that will exploit PLS' capabilities in this area.

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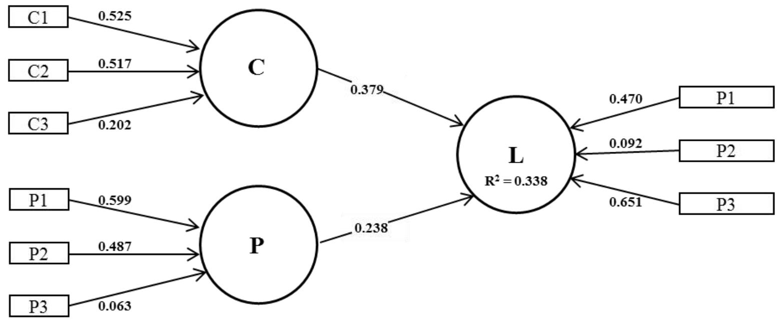
## Step 1: Split sample

## Step 2: Estimation based on training sample

Example:




## Step 3: Standardize the holdout sample data

Example:

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | C1 | C2 | C3 | P1 | P2 | P3 | L1 | L2 | L3 | $C1_{std}$ | $C2_{std}$ | $C3_{std}$ | $P1_{std}$ | $P2_{std}$ | $P3_{std}$ | $L1_{std}$ | $L2_{std}$ | $L3_{std}$ |
| 2 | 6 | 4 | 6 | 7 | 5 | 5 | 6 | 5 | 6 | -0,961 | -1,609 | 0,067 | -0,230 | -0,919 | -1,330 | -0,709 | -0,411 | -1,430 |
| 3 | 10 | 10 | 9 | 10 | 10 | 10 | 10 | 2 | 10 | 1,174 | 1,408 | 1,076 | 1,150 | 1,169 | 1,228 | 0,642 | -1,292 | 0,688 |
| 4 | 6 | 5 | 1 | 2 | 6 | 5 | 10 | 10 | 10 | -0,961 | -1,106 | -1,614 | -2,531 | -0,501 | -1,330 | 0,642 | 1,057 | 0,688 |
| 5 | 9 | 10 | 7 | 8 | 9 | 7 | 10 | 6 | 10 | 0,640 | 1,408 | 0,404 | 0,230 | 0,752 | -0,307 | 0,642 | -0,117 | 0,688 |
| 6 | 10 | 8 | 10 | 9 | 5 | 10 | 10 | 6 | 10 | 1,174 | 0,402 | 1,412 | 0,690 | -0,919 | 1,228 | 0,642 | -0,117 | 0,688 |
| 7 | 10 | 8 | 1 | 8 | 10 | 10 | 10 | 2 | 10 | 1,174 | 0,402 | -1,614 | 0,230 | 1,169 | 1,228 | 0,642 | -1,292 | 0,688 |
| 8 | 7 | 6 | 5 | 7 | 5 | 8 | 7 | 10 | 8 | -0,427 | -0,603 | -0,269 | -0,230 | -0,919 | 0,205 | -0,372 | 1,057 | -0,371 |
| 9 | 5 | 6 | 7 | 7 | 4 | 6 | 1 | 10 | 5 | -1,494 | -0,603 | 0,404 | -0,230 | -1,336 | -0,818 | -2,398 | 1,057 | -1,959 |
| 10 | 8 | 7 | 7 | 8 | 9 | 7 | 7 | 10 | 8 | 0,107 | -0,101 | 0,404 | 0,230 | 0,752 | -0,307 | -0,372 | 1,057 | -0,371 |
| 11 | 7 | 8 | 5 | 9 | 9 | 8 | 10 | 3 | 10 | -0,427 | 0,402 | -0,269 | 0,690 | 0,752 | 0,205 | 0,642 | -0,998 | 0,688 |

## Step 4: Create construct scores for the holdout sample

Example:

$$\mathrm{C} = 0.525 \cdot \mathrm{C1}_{\mathrm{std}} + 0.517 \cdot \mathrm{C2}_{\mathrm{std}} + 0.202 \cdot \mathrm{C3}_{\mathrm{std}}$$

$$\mathrm{P} = 0.599 \cdot \mathrm{P1}_{\mathrm{std}} + 0.487 \cdot \mathrm{P2}_{\mathrm{std}} + 0.063 \cdot \mathrm{P3}_{\mathrm{std}}$$

$$\mathrm{L} = 0.470 \cdot \mathrm{L1}_{\mathrm{std}} + 0.092 \cdot \mathrm{L2}_{\mathrm{std}} + 0.651 \cdot \mathrm{L3}_{\mathrm{std}}$$

| | J | K | L | M | N | O | P | Q | R | S | T | U |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | $C1_{std}$ | $C2_{std}$ | $C3_{std}$ | $P1_{std}$ | $P2_{std}$ | $P3_{std}$ | $L1_{std}$ | $L2_{std}$ | $L3_{std}$ | C | P | L |
| 2 | -0,961 | -1,609 | 0,067 | -0,230 | -0,919 | -1,330 | -0,709 | -0,411 | -1,430 | -1,323 | -0,759 | -1,302 |
| 3 | 1,174 | 1,408 | 1,076 | 1,150 | 1,169 | 1,228 | 0,642 | -1,292 | 0,688 | 1,562 | 1,786 | 0,631 |
| 4 | -0,961 | -1,106 | -1,614 | -2,531 | -0,501 | -1,330 | 0,642 | 1,057 | 0,688 | -1,402 | -2,834 | 0,847 |
| 5 | 0,640 | 1,408 | 0,404 | 0,230 | 0,752 | -0,307 | 0,642 | -0,117 | 0,688 | 1,146 | 0,575 | 0,739 |
| 6 | 1,174 | 0,402 | 1,412 | 0,690 | -0,919 | 1,228 | 0,642 | -0,117 | 0,688 | 1,110 | 0,313 | 0,739 |
| 7 | 1,174 | 0,402 | -1,614 | 0,230 | 1,169 | 1,228 | 0,642 | -1,292 | 0,688 | 0,498 | 0,875 | 0,631 |
| 8 | -0,427 | -0,603 | -0,269 | -0,230 | -0,919 | 0,205 | -0,372 | 1,057 | -0,371 | -0,590 | -0,662 | -0,319 |
| 9 | -1,494 | -0,603 | 0,404 | -0,230 | -1,336 | -0,818 | -2,398 | 1,057 | -1,959 | -1,015 | -0,930 | -2,305 |
| 10 | 0,107 | -0,101 | 0,404 | 0,230 | 0,752 | -0,307 | -0,372 | 1,057 | -0,371 | 0,086 | 0,575 | -0,319 |
| 11 | -0,427 | 0,402 | -0,269 | 0,690 | 0,752 | 0,205 | 0,642 | -0,998 | 0,688 | -0,071 | 1,062 | 0,658 |

**Figure 1: PLS cross-validation example using holdout samples (Part I)**

**Step 5: Standardize the construct scores for the holdout sample**

Example:

| | S | T | U | V | W | X |
|---|---|---|---|---|---|---|
| 1 | C | P | L | $C_{std}$ | $P_{std}$ | $L_{std}$ |
| 2 | -1,323 | -0,759 | -1,302 | -1,234 | -0,574 | -1,220 |
| 3 | 1,562 | 1,786 | 0,631 | 1,457 | 1,350 | 0,591 |
| 4 | -1,402 | -2,834 | 0,847 | -1,308 | -2,142 | 0,794 |
| 5 | 1,146 | 0,575 | 0,739 | 1,069 | 0,434 | 0,692 |
| 6 | 1,110 | 0,313 | 0,739 | 1,035 | 0,237 | 0,692 |
| 7 | 0,498 | 0,875 | 0,631 | 0,465 | 0,661 | 0,591 |
| 8 | -0,590 | -0,662 | -0,319 | -0,551 | -0,501 | -0,299 |
| 9 | -1,015 | -0,930 | -2,305 | -0,947 | -0,703 | -2,160 |
| 10 | 0,086 | 0,575 | -0,319 | 0,080 | 0,434 | -0,299 |
| 11 | -0,071 | 1,062 | 0,658 | -0,066 | 0,803 | 0,616 |

**Step 6: Create prediction scores**

Example: $$L_{pred} = 0.379 \cdot C_{std} + 0.238 \cdot P_{std}$$

| | V | W | X | Y |
|---|---|---|---|---|
| 1 | $C_{std}$ | $P_{std}$ | $L_{std}$ | $L_{pred}$ |
| 2 | -1,234 | -0,574 | -1,220 | -0,604 |
| 3 | 1,457 | 1,350 | 0,591 | 0,874 |
| 4 | -1,308 | -2,142 | 0,794 | -1,006 |
| 5 | 1,069 | 0,434 | 0,692 | 0,508 |
| 6 | 1,035 | 0,237 | 0,692 | 0,449 |
| 7 | 0,465 | 0,661 | 0,591 | 0,334 |
| 8 | -0,551 | -0,501 | -0,299 | -0,328 |
| 9 | -0,947 | -0,703 | -2,160 | -0,526 |
| 10 | 0,080 | 0,434 | -0,299 | 0,134 |
| 11 | -0,066 | 0,803 | 0,616 | 0,166 |

**Step 7: Determine the $R^2$**

Example: $$R^2 = \left(cor\left(L_{pred}, L_{std}\right)\right)^2 = 0.2415$$

**Step 8: Reporting**

**Figure 2: PLS cross-validation example using holdout samples (Part II)**