Journal of Business Research 188 (2025) 115087

Contents lists available at ScienceDirect

Journal of Business Research

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

Special issue editorial: Advanced partial least squares structural equation modeling (PLS-SEM) applications in business research

Siegfried P. Gudergan [a,b,c], Ovidiu I. Moisescu [d], Lăcrămioara Radomir [d], Christian M. Ringle [e,f], Marko Sarstedt [d,g,*]

[a] James Cook University, Australia
[b] Aalto University, Finland
[c] Vienna University of Economics and Business, Austria
[d] Babeș-Bolyai University, Romania
[e] Hamburg University of Technology, Germany
[f] James Cook University, Australia
[g] Ludwig-Maximilians University Munich, Germany

1. Introduction

This special issue comprises a series of advanced applications of and methodological developments concerning PLS-SEM in business research. PLS-SEM,[1] introduced by Wold (1975, 1982) and Lohmöller (1989), models the structural relationships between constructs (i.e., the latent variables) as empirical approximations of theoretical concepts. Each construct is operationalized by a measurement model with a set of indicators (i.e., observed variables). The PLS-SEM method estimates the entire model with the aim of maximizing the explained variance of the dependent constructs in the structural model and of the indicators in the constructs' measurement models (Lohmöller, 1989; Wold, 1982).[2]

Fig. 1 shows a sample PLS path model that several textbooks and research articles use to illustrate the method (e.g., Hair et al., 2022). The model maps the impact of corporate reputation, represented by its two dimensions, likeability (*LIKE*) and competence (*COMP*), on customer satisfaction (*CUSA*) and customer loyalty (*CUSL*) (Schwaiger, 2004; Schwaiger et al., 2010). While *CUSA* is measured with a single item, the other three constructs are operationalized with three reflective items each.

To obtain the PLS-SEM results in Fig. 1, we estimated the model with the standard PLS-SEM algorithm (Lohmöller, 1989; Wold, 1982) using the dataset provided by Sarstedt et al. (2023b) and the statistical software SmartPLS (Ringle et al., 2024). The algorithm follows a three-stage process. Stage 1 computes the construct scores by means of a four-step procedure, which draws on the indicator data to iteratively estimate the indicator weights (i.e., the weights used to compute the construct scores) and the structural model relationships (i.e., the path coefficients). After convergence, stages 2 and 3 use the final construct scores from stage 1 as input to estimate the final set of model parameters, including R^2 values and construct correlations—see, for example, Hair et al. (2022, Chapter 3), Lohmöller (1989, Chapter 2), Sarstedt et al. (2021), and Wold (1982) for more details on the PLS-SEM algorithm.

To assess the quality of our results, we draw on a series of commonly used metrics and procedures (e.g., Hair et al., 2022). For example, inference testing draws on the bootstrapping routine while predictive power assessment builds on *k*-fold cross-validation, which is routinely used in other contexts such as machine learning. Applying these metrics and procedures to the corporate reputation model and data, we find that all measures are reliable and valid and that the model has sufficient levels of explanatory and predictive power with regard to its key target construct *CUSL*. As shown in Fig. 1, results from bootstrapping suggest

* Corresponding author at: Ludwig-Maximilians University Munich, Germany.
E-mail addresses: siggi.gudergan@jcu.edu.au (S.P. Gudergan), ovidiu.moisescu@econ.ubbcluj.ro (O.I. Moisescu), lacramioara.radomir@econ.ubbcluj.ro (L. Radomir), c.ringle@tuhh.de (C.M. Ringle), sarstedt@lmu.de (M. Sarstedt).

[1] In the literature, PLS-SEM (e.g., Hair et al., 2011; Radomir et al., 2023; Ringle et al., 2023; Sarstedt et al., 2022b) is also referred to as path models with latent variables (Wold, 1975), partial least squares (PLS; Wold, 1985), latent variable path modeling with partial least squares (Lohmöller, 1989), PLS path modeling (e.g., Esposito Vinzi et al., 2010; Tenenhaus et al., 2005), and the PLS approach to structural equation modeling (e.g., Chin, 1998).

[2] This special issue focuses on PLS-SEM, which is a component- or composite-based approach to PLS-SEM (e.g., McDonald, 1996; Tenenhaus et al., 2005); note that we use the terms composites and components interchangeably throughout this research (see also Hwang et al., 2020). The generalized structured component analysis (Hwang & Takane, 2004, 2014) is a viable alternative to PLS-SEM (Cho et al., 2023; Hwang et al., 2020).

https://doi.org/10.1016/j.jbusres.2024.115087
Received 27 September 2024; Received in revised form 18 November 2024; Accepted 18 November 2024
Available online 28 November 2024

Table 1
Methodological advancements in PLS-SEM.

Data and algorithms		
Methodological Advancements	**Explanation and key sources**	**Papers in this special issue**
Binary and categorical data	Researchers sometimes use binary/categorical data in their studies (e.g., Fornell et al., 2020; Morgeson et al., 2023). Bertholet and Wold (1984) and Lohmöller (1989) proposed approaches that allow researcher to use categorical and binary data in PLS-SEM (see also Bodoff & Ho, 2016; Hair et al., 2019b). Furthermore, Becker et al. (2023) advance binary moderators' use in PLS-SEM, while Jakobowicz and Derquenne (2007), and Henseler et al. (2016a) elaborated further on its use in respect of categorical data (see also Hair et al., 2022).	–
Ordinal data	Ordinally scaled variables (e.g., Likert scales) meet the PLS-SEM algorithm's requirements, provided researchers can justify the scales' equidistance (i.e., measurement on a quasi-metric scale; Ringle et al., 2023). If equidistance is not given, researchers ought to consider reverting to specialized nonmetric and ordinal PLS-SEM variants (Cantaluppi & Boari, 2016; Russolillo, 2012; Schuberth et al., 2018b).	–
Weighted PLS-SEM (WPLS) algorithm	The sample should be representative of the population of interest to draw valid inferences (Sarstedt et al., 2018). Researchers could use a weighting vector with sampling weights to ensure that the sample structure meets that of the overall population in respect of key sampling variables. Becker and Ismail (2016) suggested using the WPLS algorithm to incorporate sampling weights into the PLS-SEM estimation (see also Cheah et al., 2021; Hair et al., 2022).	–
Lohmöller's extended PLS-SEM algorithm	The extended PLS-SEM algorithm that Lohmöller (1989) introduced, uses a covariance matrix as data input. It offers key advantages, such as additional modeling options to link an indicator to more than one latent variable. This capability can facilitate exploratory PLS-SEM analyses. It also allows researchers to constrain the relationships between the exogenous constructs in the structural model (e.g., to zero).	–
Composite model estimations' mimicking of common factors	Whereas PLS-SEM assumes composite models in its parameter estimation, covariance-based SEM (CB-SEM) implies the use of common factor models (e.g., Jöreskog & Wold, 1982; Lohmöller, 1989; Rigdon, 2012; Rigdon et al., 2017; Sarstedt et al., 2016). If researchers do not use CB-SEM and apply PLS-SEM to mimic common factor results, they can consider other techniques, such as consistent PLS (PLSc-SEM; Dijkstra, 2014; Dijkstra & Henseler, 2015; Dijkstra & Schermelleh-Engel, 2014), its PLSe1/PLS2e extensions (Bentler & Huang, 2014; Huang, 2013), and the Cronbach α-based approach by Yuan et al. (2020).	–
Results assessment		
Methodological Advancements	**Explanation and key sources**	**Papers in this special issue**
Confirmatory tetrad analysis (CTA-PLS)	A measurement model misspecification can render SEM results invalid (e.g., Jarvis et al., 2003). Gudergan et al. (2008) introduced the confirmatory tetrad analysis in PLS-SEM to distinguish between reflectively and formatively measured constructs. On the basis of the model-implied vanishing tetrads' bootstrap-based test (Bollen & Ting, 1998; Hair et al., 2024c), researchers can substantiate their theoretically established measurement model empirically, thereby avoiding measurement model misspecifications.	Ji et al. (2024); Manzi-Puertas et al. (2024); Troiville (2024)
Heterotrait-monotrait ratio of correlations (HTMT)	Discriminant validity testing ensures that constructs, which are conceptually distinct, also differ empirically (e.g., Voorhees et al., 2016). Henseler et al. (2015) showed that the commonly used Fornell-Larcker approach (Fornell & Larcker, 1981) has validity issues and, instead, suggested using the HTMT criterion. Based on the Franke and Sarstedt (2019) findings, Hair et al. (2022) suggest that the HTMT criterion should be significantly below 0.85 (or 0.90 if the constructs are conceptually similar). More recent research has proposed variants of the original HTMT metrics—see Ringle et al. (2023) for a discussion.	Capeau et al. (2024); Cassia and Magno (2024); Ji et al. (2024); Kurtaliqi et al. (2024); Mansoor et al. (2024); Manzi-Puertas et al. (2024); Richter and Tudoran (2024); Riggs et al. (2024); Shela et al. (2024); Troiville (2024)
Necessary condition analysis (NCA)	A necessity logic implies that an outcome (or outcome level) can only be achieved if a necessary condition is in place (or has achieved a certain level). A necessary condition analysis (NCA; Dul, 2016, 2020) can identify such must-have conditions. In a PLS-SEM context, the NCA reveals the necessary independent constructs in the structural model that facilitate a certain outcome level for a dependent construct (Aldhamiri et al., 2024; Hair, Sarstedt et al., 2024c; Richter et al., 2020). The NCA therefore complements PLS-SEM's sufficiency logic (Hauff et al., 2024; Richter et al., 2023), which allows researchers to identify should-have conditions.	Cassia and Magno (2024)
Common method variance (CMV)	Common method variance's (CMV's) common methods bias arises from the correlations between the variables measured with the same method (e.g., in self-reported surveys), which can inflate the estimated coefficients (Podsakoff et al., 2003; Spector & Brannick, 2010). Researchers have long debated whether CMV poses a significant problem in statistical analyses in general (e.g., Pace, 2009; Spector, 2006). Chin	Capeau et al 2024; Ji et al. (2024); Mansoor et al. (2024); Manzi-Puertas et al. (2024); Riggs et al. (2024); Shela et al. (2024); Troiville (2024)

(*continued on next page*)

Table 1 (*continued*)

Data and algorithms		
Methodological Advancements	**Explanation and key sources**	**Papers in this special issue**
	et al. (2012) demonstrated that an unmeasured latent method construct (ULMC) approach cannot accurately detect common method bias in PLS-SEM (or CB-SEM), while Chin et al.'s (2013) measured latent marker variable (MLMV) approach showed some promise in addressing this issue. Kock (2015), instead, suggested using a collinearity-based assessment approach.	
Endogeneity	Endogeneity poses a significant challenge for regression models in studies with non-experimental data, potentially leading to biased and inconsistent coefficients, and rendering them causally uninterpretable (e.g., Sande & Ghosh, 2018; Zaefarian et al., 2017). To overcome certain shortcomings of the instrumental variable (IV) approach (Wooldridge, 2010), and to deal with endogeneity in regression models (Rossi, 2014), Park and Gupta (2012) introduced an IV-free Gaussian copula approach, which further research extended (e.g., Liengaard et al., 2024). Hult et al. (2018) introduced the Gaussian copula approach to PLS-SEM (see also Becker et al., 2022).	Ji et al. (2024); Manzi-Puertas et al. (2024); Riggs et al. (2024); Shela et al. (2024); Troiville (2024); Vaithilingam et al. (2024)
Model fit	Researchers using CB-SEM routinely assess the model fit drawing on quantitative metrics of the divergence between the sample and the model-implied covariances (e.g., Bentler & Bonett, 1980). The PLS-SEM algorithm's aim is, however, not to minimize this divergence, which casts doubt on these metrics' usefulness for PLS-SEM (Hair et al., 2019d). Lohmöller (1989) discussed model fit in PLS-SEM in some detail; later, Esposito Vinzi et al. (2010), Henseler et al. (2016a), and Schuberth et al. (2023) revitalized this discussion (see also Henseler & Sarstedt, 2013), introducing model fit metrics for PLS-SEM – see Ringle et al. (2023) for a discussion.	Mansoor et al. (2024); Riggs et al. (2024)
Predictive power assessment	Establishing the predictive power of a model is a key pillar of regression-based methods, including PLS-SEM (Hofman et al., 2017; Hofman et al., 2021; Shmueli, 2010; Shmueli & Koppius, 2011). In business research, where management recommendations often have a predictive focus (Hair & Sarstedt, 2021; Sarstedt & Danks, 2022), it is essential to evaluate the predictive power of a PLS path model (Hair, 2021; Hair et al., 2022). To this end, techniques such as the $\text{PLS}_{\text{predict}}$ procedure (Shmueli et al., 2016; Shmueli et al., 2019) and the cross-validated predictive ability test (CVPAT; Liengaard et al., 2021; Sharma et al., 2023a) provide researchers with appropriate methods to assess the predictive power of their PLS path models.	Capeau et al. (2024); Cassia and Magno (2024); Ji et al. (2024); Kurtaliqi et al. (2024); Mansoor et al. (2024); Manzi-Puertas et al. (2024); Richter and Tudoran (2024); Riggs et al. (2024); Shela et al. (2024); Troiville (2024)
Model comparisons	Theories frequently give rise to different model configurations. Researchers should compare alternative models on empirical grounds to identify the most appropriate one. To do so, they can rely on information-theoretic model selection criteria, such as the Bayesian information criterion (Schwarz, 1978) and the CVPAT (Liengaard et al., 2021; Sharma et al., 2023a).	Capeau et al. (2024); Richter and Tudoran (2024); Troiville (2024)
Confirmatory composite analysis (CCA)	A confirmatory composite analysis (CCA) is a series of steps that researchers can execute to assess the PLS-SEM results. Two approaches to CCA share many properties, but differ in others, most notably in the model fit and predictive power assessment roles. Specifically, Hair et al. (2019a) and Hair et al. (2020) emphasized the role of predictive power assessments, while Schuberth et al. (2018a) and Henseler and Schuberth (2020) focused more on model fit assessments. Both approaches have merit and researchers should draw on the approach that best fits their requirements.	Ji et al. (2024) Note: While all authors validated their models using metrics proposed in the CCA variants, only Ji et al. (2024) made explicit reference to the CCA.
Importance-performance map analysis (IPMA)	An importance-performance map analysis (IPMA; e.g., Martilla & James, 1977; Slack, 1994) compares the total effect (i.e., importance) and the average value (i.e., performance) of a target construct's antecedents (Höck et al., 2010; Martensen & Grønholdt, 2003). Researchers can, for instance, identify highly important, but low performance constructs that enable managers to prioritize their activities. Recent research introduced the combined IPMA, which adds an additional dimension to the map that identifies whether antecedent constructs are necessary to achieve a certain outcome level of the dependent construct (Hauff et al., 2024; Sarstedt et al., 2024b).	Capeau et al. (2024); Cassia and Magno (2024)
Extended modeling and additional validity and robustness checks		
Methodological Advancements	**Explanation and key sources**	**Papers in this special issue**
Control variables	To ensure that the path coefficient estimates are not biased, research models routinely include control variables (e.g., Klarmann & Feurer, 2018). In PLS-SEM, control variables can be included by using single-item constructs added to the structural model (Hair et al., 2022)—one for each control variable. Interaction terms can also be addressed with a procedure that is similar to running a moderator analysis (Becker et al., 2018).	Ji et al. (2024); Mansoor et al. (2024); Manzi-Puertas et al. (2024); Riggs et al. (2024); Shela et al. (2024)

(*continued on next page*)

Table 1 (*continued*)

Data and algorithms		
Methodological Advancements	**Explanation and key sources**	**Papers in this special issue**
Mediation and conditional process analysis	Mediation concerns parts of a model in which one or more mediator constructs explain the processes through which an exogenous construct influences an endogenous construct (Baron & Kenny, 1986). By following Zhao et al.'s (2010) procedure, researchers can carry out a mediation analysis in PLS-SEM (Memon et al., 2018; Nitzl et al., 2016). This analysis can be extended to multiple mediators, or to a combination of one or more mediators and moderators (e.g., by considering a moderated mediation analysis), thereby giving rise to a conditional process analysis (Cheah et al., 2021; Hayes, 2022). Bootstrapping allows researchers to assess the various types of mediations and conditional process analyses directly in PLS-SEM (Sarstedt et al., 2020).	Capeau et al. (2024); Cassia and Magno (2024); Mansoor et al. (2024); Manzi-Puertas et al. (2024); Riggs et al. (2024); Shela et al. (2024); Troiville (2024)
Higher-order constructs	Higher-order constructs represent theoretical concepts on different levels of abstraction. While higher-order constructs usually take the form of second-order constructs with a higher-order and a series of lower-order components, they can be extended to third-order or fourth-orders (Ringle et al., 2012; Wetzels et al., 2009). The modeling, estimation, results analysis, and the reporting of higher-order models all come with a series of challenges, which Sarstedt et al. (2019) discussed. For example, in order to identify the higher-order construct, researchers should rely on the disjoint two-stage approach (Becker et al., 2023; Hair et al., 2024c).	Capeau et al. (2024); Manzi-Puertas et al. (2024); Riggs et al. (2024); Troiville (2024)
Moderation / analysis of interaction effects	A moderator analysis allows researchers to assess observed heterogeneity in selected relationships within the structural model (Baron & Kenny, 1986). A moderator indicates how a relationship's strength increases or decreases between constructs when the moderator level changes (e.g., the moderator's average level versus its level above or below the average). To implement it in PLS-SEM, researchers can draw on several approaches differing in their operationalization of the interaction term, which quantify the moderation's strength (Fassott et al., 2016; Hair et al., 2022; Henseler & Fassott, 2010; Memon et al., 2019). Of these approaches, researchers should use the two-stage approach (Becker et al., 2018)—especially when using binary moderators (Becker et al., 2023).	Cassia and Magno (2024); Ji et al. (2024); Mansoor et al. (2024); Manzi-Puertas et al. (2024); Richter and Tudoran (2024); Riggs et al. (2024); Shela et al. (2024)
Measurement invariance	Measurement invariance refers to whether in different conditions of observing and studying phenomena (e.g., different groups of respondents), measurement operationalizations yield measures of the same concept (Byrne et al., 1989; Millsap, 2011; Vandenberg & Lance, 2000). Failure to establish measurement invariance can have adverse consequences for any implications drawn from the analysis of different data groups. Henseler et al. (2016b) introduced the measurement invariance of composite models (MICOM; see also Hair et al., 2024c) approach. Researchers need to apply the MICOM approach to establish whether measurement invariance is present prior to running a multigroup analysis in PLS-SEM.	Cassia and Magno (2024); Kurtaliqi et al. (2024); Ji et al. (2024); Liengaard (2024); Manzi-Puertas et al. (2024)
Multigroup analysis	Multigroup analysis enables the assessment of whether coefficients, especially for structural relationships, differ significantly across groups (MGA; Picón Berjoyo et al., 2016; Qureshi & Compeau, 2009). Different approaches serve multigroup analyses in PLS-SEM (Matthews, 2017; Sarstedt et al., 2011b), including a permutation-based variant (Chin & Dibbern, 2010), which recent research identified as particularly suitable (Klesel et al., 2022). These approaches can also be applied to more than two groups (Cheah et al., 2023; Hair et al., 2024c).	Cassia and Magno (2024); Ji et al. (2024); Kurtaliqi et al. (2024); Liengaard (2024); Manzi-Puertas et al. (2024)
Nonlinear relationships	The majority of conceptual frameworks, which form the basis for cause-and-effect relationships in PLS-SEM, presume that constructs have linear impacts on one another. In certain scenarios, this assumption may not be valid, because the hypothesized relations are nonlinear by nature (e.g., Ahrholdt et al., 2019). Researchers have long noted PLS-SEM's ability to accommodate nonlinear effects (Wold, 1973, 1982; Wold & Lyttkens, 1969). While different types of nonlinearities can be assumed, quadratic effects are the most commonly considered ones in applied research. Basco et al. (2021), Hair et al. (2024c), and Rigdon et al. (2010) provide detailed explanations of how to analyze quadratic and s-shaped nonlinear effects in PLS-SEM.	Manzi-Puertas et al. (2024); Richter and Tudoran (2024); Riggs et al. (2024); Vaithilingam et al. (2024)
Model specification search	Researchers have introduced several approaches to automate SEM's model specification, including the tabu search algorithm (Marcoulides et al., 1998), the genetic search algorithm (Marcoulides & Drezner, 2001), and the ant colony optimization algorithm (Marcoulides & Drezner, 2003). In a PLS-SEM context, researchers have applied Cohen's path method to explore path directionality (Callaghan et al., 2007), and a fuzzy-set qualitative comparative analysis (fsQCA) (e.g., Carlson et al., 2019; Gelhard et al., 2016; Rasoolimanesh et al., 2021).	–
Latent class analysis	Latent class analyses allow researchers to uncover unobserved heterogeneity (Sarstedt et al., 2022c), which, if not controlled for, can adversely impact the validity of results (Becker et al., 2013; Jedidi et al., 1997). Options for conducting a latent class analysis in PLS-SEM include	Ji et al. (2024); Manzi-Puertas et al. (2024); Vaithilingam et al. (2024)

(*continued on next page*)

Table 1 (*continued*)

Data and algorithms		
Methodological Advancements	**Explanation and key sources**	**Papers in this special issue**
	finite mixture partial least squares (FIMIX-PLS; Hahn et al., 2002; Hair, Sarstedt et al. 2016; Matthews et al., 2016; Sarstedt et al., 2011a), prediction-oriented segmentation (Becker et al., 2013), genetic algorithm segmentation (Ringle et al., 2014a, 2014b), and iterative reweighted regression segmentation (Schlittgen et al., 2016). Rather than relying solely on one of them, researchers should use such methods in combination to leverage their respective strengths in terms of addressing the critical issue of unobserved heterogeneity effectively (Hair et al., 2024c; Ringle et al., 2010; Sarstedt et al., 2022; Sarstedt et al., 2017).	

that all path coefficients are significant (as indicated by the *p*-values in the brackets) and that *CUSA* has the strongest (standardized) effect (0.552) on *CUSL*, followed by *LIKE* (0.240) and *COMP* (0.154). For literature explaining the results assessment, see, for example, Guenther et al. (2023), Hair et al. (2022; Chapters 4–6), Hair et al. (2019c), Legate et al. (2023), and Sarstedt et al. (2021).

This small example already suggests that PLS-SEM allows researchers to gain a holistic understanding of the causal-predictive relationships between constructs in a causal chain system, even in relatively complex models (Chin et al., 2020; Jöreskog & Wold, 1982; Sarstedt et al., 2021; Wold, 1982). The results identify the indicators and constructs that exhibit strong relationships within the model, thus highlighting their importance for explaining and predicting changes and outcomes in the model's dependent variables (Hair et al., 2022, Chapter 6; Sarstedt et al., 2021). In doing so, PLS-SEM combines the strengths of both exploratory and confirmatory research (Sharma et al., 2024). Moreover, PLS-SEM allows validating the model's predictive power statistically. This characteristic is particularly important to substantiate managerial recommendations from PLS-SEM results, since such findings are predictive by nature (Sarstedt & Danks, 2022).

PLS-SEM has gained increased acceptance and recognition across various disciplines (e.g., management, medicine, engineering, psychology, political and environmental sciences; for an overview see Table 1 in Cepeda-Carrión et al., 2022; see also Table 1.1 in Hair et al., 2021) including publications in different fields of business research (e.g., Petter & Hadavi, 2023), for instance marketing (e.g., Guenther et al., 2023; Sarstedt et al., 2022a), and in textbooks on key research methods in the social sciences (e.g., Hair et al., 2019a). Simultaneously, PLS-SEM's growing popularity has drawn criticism from certain researchers (e.g., Evermann & Rönkkö, 2023; Rönkkö & Evermann, 2013; Rönkkö et al., 2016; Rönkkö et al., 2015), which their counterparts frequently challenged (e.g., Henseler et al., 2014; Marcoulides et al., 2012; Petter, 2018; Rigdon, 2023; Russo & Stol, 2023; Sarstedt et al., 2016; Sharma, 2023b); also see the criticism by Rönkkö et al. (2023) and the rejoinder by Yuan (2023) as well as the later responses by Hair et al. (2024a) and Hair et al. (2024b). Recently, Cook and Forzani (2023) countered compellingly the criticism concerning PLS-SEM by offering a comprehensive overview highlighting its promising potential. These authors characterize PLS-SEM as an envelope method offering a new perspective for studying and characterizing bias, thereby dispelling the common misconceptions that had fueled the debates on the method.

Overall, PLS-SEM, like any methodological approach, not only has inherent advantages, but also disadvantages (e.g., Hair et al., 2024a; Marcoulides & Saunders, 2006; Rigdon, 2016; Sarstedt et al., 2023a). Petter and Hadavi (2021, p. 10) note that: "PLS offers great power for researchers who wish to use a SEM-based approach to evaluate a research model. However, with the great power of PLS also comes great responsibility. Scholars should determine if PLS is appropriate to use within their context, and scholars should explain their rationale for employing PLS for data analyses." We couldn't agree more (e.g., Rigdon et al., 2017; Ringle et al., 2023; Sarstedt et al., 2024a).

In recent years, researchers have made significant strides in enhancing and broadening the PLS-SEM method's capabilities, and in overcoming its limitations. These advancements not only facilitate more proficient business research being produced, but are also pertinent across various other research disciplines. As detailed in Table 1, PLS-SEM researchers have already made considerable progress in terms of expanding the method's capabilities and solidifying its position as a valuable tool for multimethod analyses, which combine different multivariate analysis techniques or build on qualitative research results. These advances have substantially increased the method's application scope, making it an important business analytics tool for addressing a plethora of research questions in business and other fields of scientific inquiry. Additional advances include, for example, the global PLS algorithm (Hwang & Cho, 2020), missing value treatment options in the context of PLS-SEM analyses (Grimm & Wagner, 2020; Wang et al., 2022), PLS-SEM and agent-based simulation (Schubring et al., 2016), longitudinal PLS-SEM analyses (Lohmöller, 1989; Roemer, 2016), and machine learning in conjunction with PLS-SEM (Richter & Tudoran, 2024), which considers artificial neural networks (e.g., Abbasi et al., 2021; Mkedder & Bakır, 2023). Researchers have also identified further requirements to develop the method, such as integrating longitudinal and panel data analyses into PLS-SEM, delving into non-recursive models, incorporating model constraints, and developing an exploratory PLS-SEM approach in which an indicator relates to multiple constructs.

The objective of this special issue on *Advanced PLS-SEM Applications in Business Research* is to introduce these advances to a wider audience. It demonstrates the application of these methods in generating new insights on existing or refined models and theories. Additionally, it outlines novel methodological advances of the PLS-SEM method. Through the 13 articles in this special issue, the contributions to the advances outlined in Table 1 are further detailed or expanded. In particular:

- Adler et al. (2023) acknowledge that concerns about reproducibility, stemming from underpowered studies or excessive analytical freedom, have led to calls for greater research transparency—this also holds for studies using PLS-SEM. The authors find that very few PLS-SEM-based studies apply open science practices and therefore call for their broader adoption. To support this process, the authors propose a preregistration template to foster transparency and, consequently, strengthen confidence in findings derived from PLS-SEM–based studies.
- In another article in this special issue, Richter and Tudoran (2024) suggest embedding maximum likelihood (ML) algorithms in PLS-SEM. The proposed four-step procedure combines PLS-SEM with ML algorithms. In a first step, a standard PLS-SEM model is run to estimate and assess measurement models, followed by an application of ML algorithms to the extracted latent variable scores in order to assess structural relationships, and identify new ones. Using theoretical plausibility as a criterion, the procedure next evaluates alternative models before applying the standard PLS-SEM method and undertaking a comparison by using a prediction-oriented test with the baseline model.

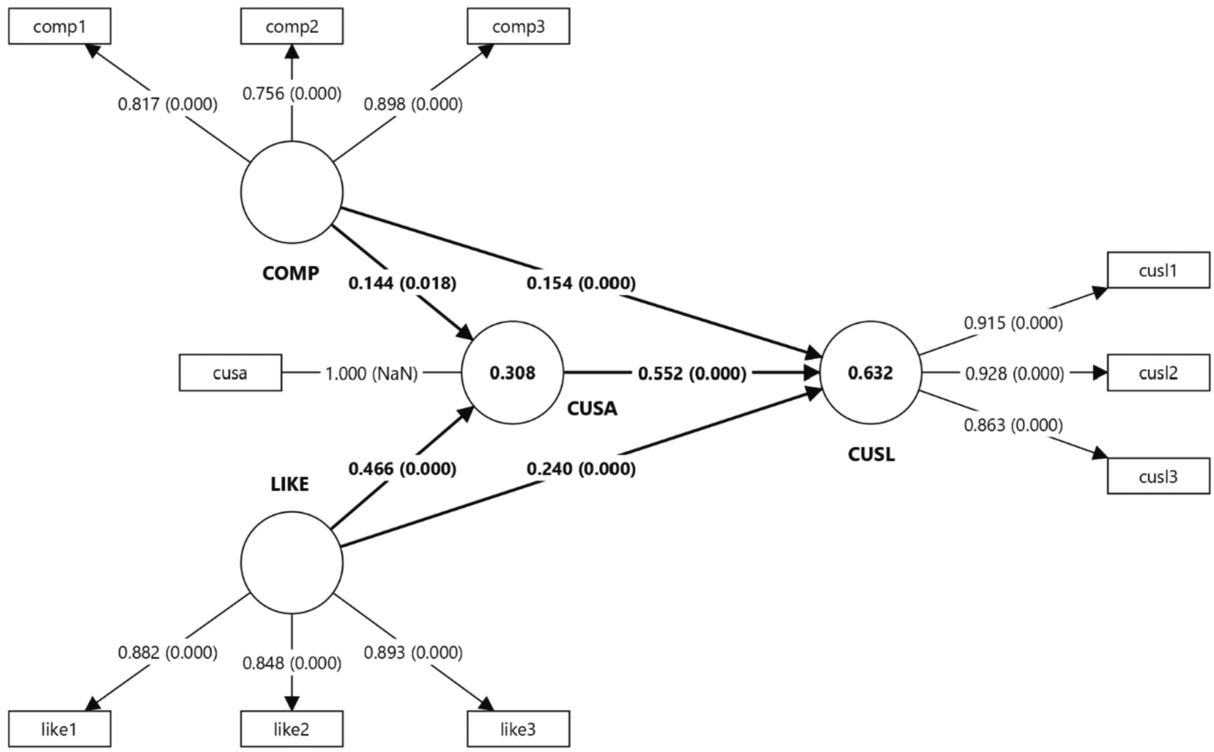


Fig. 1. PLS-SEM results for the simple corporate reputation example. Note: circles = constructs; rectangles = indicators; values on the path relationships = standardized coefficients with bootstrap p values in brackets; values in the circles = R^2 values.

- Employing PLS-SEM in combination with NCA, Cassia and Magno (2024) assess arguments that draw on self-determination theory (SDT) and the notion of intrinsic and extrinsic motivations to understand the use of anti–food waste apps. The findings confirm that SDT has strong power in terms of predicting use, with NCA results indicating that both intrinsic and extrinsic motivations have complementary, separate effects, which drive app usage.
- Kurtaliqi et al. (2024) extend the use of PLS-SEM by leveraging exploratory and intervention approaches. Using three retail case studies, they demonstrate that using exploratory studies can refine PLS-SEM model development, that interventions can provide real-world insights, and that qualitative efforts enable development of fine-grained interventions.
- Turning to a review of prior PLS-SEM applications in business research, published between 2016 and 2021, Vaithilingam et al. (2024) outline concerns about robustness checks being neglected and ensuing potential validity threats to the findings. They therefore call for increased rigor in the use of PLS-SEM, which, they suggest, researchers can support by adopting selected improvements.
- Manzi-Puertas et al. (2024) employ advanced PLS-SEM procedures to examine the relationship between resourceful behaviors—such as financial bootstrapping, bricolage, and improvisation—and innovation in nascent entrepreneurship. Grounded in the resource-based view and entrepreneurial learning theory, the study analyzes data from two cohorts of Spanish student entrepreneurs. The findings reveal that the link between financial bootstrapping and innovation is informed by bricolage during the development and the exploitation stages. The study emphasizes that student entrepreneurs, when identifying innovation opportunities, also need to effectively integrate and leverage all available resources when innovating.
- Riggs et al. (2024) delve into the relationship between information technology business value and sustainable practices, particularly in the context of the circular economy. Grounded in information systems capabilities and contingency theory, the study demonstrates that circular economy practices mediate the relationship between information systems capabilities and business performance. Furthermore, the findings reveal that environmental uncertainty moderates both the impact of circular economy practices on business performance and their role as mediators in the link between information systems capabilities and business performance.
- Liengaard (2024) addresses the challenge of ensuring measurement invariance in PLS-SEM, essential for meaningful comparisons across groups or time. This research introduces an innovative approach that enhances measurement invariance testing in PLS-SEM by incorporating statistical tests for latent mean comparisons, accommodating longitudinal studies, and enabling simultaneous assessment across multiple groups. Additionally, the study offers a novel approach for handling measurement invariance rejections in large-sample studies. Beyond its important methodological contributions, this article provides practical guidelines for assessing measurement invariance and demonstrates their application through an empirical study.
- Mansoor et al. (2024) investigate the growing trend of luxury brands targeting the middle class through masstige marketing, which merges luxury and mass appeal to broaden brand accessibility. Drawing on masstige theory, the research examines the influence of symbolic motivations—snob, Veblen, and bandwagon—on masstige purchase intention, with inspiration toward masstige acting as a mediator. Two independent studies involving clothing and car brand customers support the hypothesized relationships, indicating that symbolic motivations are significant predictors of masstige purchase intention both directly and indirectly through inspiration toward masstige. The findings also highlight differences in the influence of symbolic motivations on inspiration toward masstige and purchase intentions between clothing and car brand customers, as well as a notable interaction between brand credibility and the inspiration toward masstige in enhancing masstige purchase intention, particularly that of car brand customers.
- Capeau et al. (2024) examine consumer engagement in making or do-it-yourself activities. By integrating consumer engagement theories with service-dominant logic and conservation of resources

theory, the study identifies key resources that influence consumer engagement in making activities through qualitative interviews and quantitative analysis. Employing PLS-SEM and the CVPAT, the researchers empirically validate their hypotheses. Additionally, the authors provide actionable insights for decision-makers in the maker ecosystem through an IPMA.

- Troiville (2024) examines the relationship between retailer brand equity, consumer attitudes, word-of-mouth communication, and consumer loyalty in the home improvement retail sector. Using PLS-SEM, the study confirms that consumer attitudes and word-of-mouth sequentially mediate the link between retailer brand equity and consumer loyalty. The findings suggest that this refined model offers retail managers a more precise framework for understanding the impact of brand equity on marketing performance and predicting customer loyalty.
- Shela et al. (2024) argue that modern organizations require key capabilities to navigate uncertain and challenging environments, with human capital, financial resources, and information technology (IT) infrastructure being critical drivers of resilience. Their research empirically tests collective mindfulness as a capability that transforms organizational resources into resilience, using an extended PLS-SEM method with a predictive composite overfit analysis (COA) framework. The findings indicate that firm size moderates the relationship between financial resources and collective mindfulness, thereby enhancing research rigor and theoretical development.
- Finally, the study by Ji et al. (2024) explores how firms leverage internal research and development (R&D) and external customer knowledge, particularly from social media, to enhance innovation performance. The study focuses on the interplay between a firm's absorptive capacity, R&D intensity, and customer knowledge sourced from social media. The findings suggest that firms with low R&D intensity benefit more from developing strong absorptive capacity to capitalize on social media customer knowledge, while high R&D intensity firms may not need to prioritize absorptive capacity as much.

All articles in this special edition can be accessed via this link: https://www.sciencedirect.com/journal/journal-of-business-research/special-issue/10CTN3HZXVV.

We would like to thank the authors for their dedication and insightful contributions, which have made this special issue of the *Journal of Business Research* (*JBR*) possible and advance the current state of research significantly. We would also like to express our gratitude to the reviewers. They have contributed their time and expertise, while their detailed and constructive feedback has significantly improved the submitted manuscripts' quality. Furthermore, we acknowledge the unwavering support of Naveen Donthu and Anders Gustafsson, the former *JBR* editors-in-chief, and Dipayan Biswas and Mirella Kleijnen, the current *JBR* editors-in-chief, who entrusted us with the responsibility of curating this special issue. Their faith in our work and guidance has been invaluable, and we sincerely appreciate their generous support.

CRediT authorship contribution statement

Siegfried P. Gudergan: Writing – review & editing, Validation, Supervision, Conceptualization. **Ovidiu I. Moisescu:** Writing – review & editing, Validation, Supervision, Conceptualization. **Lăcrămioara Radomir:** Writing – review & editing, Validation, Supervision, Project administration, Conceptualization. **Christian M. Ringle:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Conceptualization. **Marko Sarstedt:** Writing – review & editing, Validation, Supervision, Conceptualization.

Acknowledgement

Christian M. Ringle acknowledges a financial interest in the statistical software SmartPLS (https://www.smartpls.com).

Data availability

In this editorial, we present an example using a publicly available dataset provided by Sarstedt et al. (2023b).

References

Abbasi, G. A., Tiew, L. Y., Tang, J., Goh, Y.-N., & Thurasamy, R. (2021). The Adoption of Cryptocurrency as a Disruptive Force: Deep Learning-based Dual Stage Structural Equation Modelling and Artificial Neural Network Analysis. *PLOS ONE, 16*(3).

Adler, S. J., Sharma, P. N., & Radomir, L. (2023). Toward Open Science in PLS-SEM: Assessing the State of the Art and Future Perspectives. *Journal of Business Research, 169*, Article 114291.

Ahrholdt, D. C., Gudergan, S. P., & Ringle, C. M. (2019). Enhancing Loyalty: When Improving Consumer Satisfaction and Delight Matters. *Journal of Business Research, 94*(1), 18–27.

Aldhamiri, A., Carlson, J., Vilches-Montero, S., Rahman, S. M., & Gudergan, S. P. (2024). What Drives Higher Active Customer Engagement in Luxury Brands' Social Media? Measurement and Contingencies. *Journal of Retailing and Consumer Services, 79*, Article 103804.

Baron, R. M., & Kenny, D. A. (1986). The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic and Statistical Considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182.

Basco, R., Hair, J. F., Ringle, C. M., & Sarstedt, M. (2021). Advancing Family Business Research Through Modeling Nonlinear Relationships: Comparing PLS-SEM and Multiple Regression. *Journal of Family Business Strategy, 100457*.

Becker, J.-M., Cheah, J. H., Gholamzade, R., Ringle, C. M., & Sarstedt, M. (2023). PLS-SEM's Most Wanted Guidance. *International Journal of Contemporary Hospitality Management, 35*(1), 321–346.

Becker, J.-M., & Ismail, I. R. (2016). Accounting for Sampling Weights in PLS Path Modeling: Simulations and Empirical Examples. *European Management Journal, 34*(6), 606–617.

Becker, J.-M., Proksch, D., & Ringle, C. M. (2022). Revisiting Gaussian Copulas to Handle Endogenous Regressors. *Journal of the Academy of Marketing Science, 50*, 46–66.

Becker, J.-M., Rai, A., Ringle, C. M., & Völckner, F. (2013). Discovering Unobserved Heterogeneity in Structural Equation Models to Avert Validity Threats. *MIS Quarterly, 37*(3), 665–694.

Becker, J.-M., Ringle, C. M., & Sarstedt, M. (2018). Estimating Moderating Effects in PLS-SEM and PLSc-SEM: Interaction Term Generation*Data Treatment. *Journal of Applied Structural Equation Modeling, 2*(2), 1–21.

Bentler, P. M., & Bonett, D. G. (1980). Significance Tests and Goodness of Fit in the Analysis of Covariance Structures. *Psychological Bulletin, 88*(3), 588–606.

Bentler, P. M., & Huang, W. (2014). On Components, Latent Variables, PLS and Simple Methods: Reactions to Rigdon's Rethinking of PLS. *Long Range Planning, 47*(3), 138–145.

Bertholet, J.-L., & Wold, H. (1984). Recent Developments on Categorical Data Analysis by PLS Modeling. In I. Seminar (Ed.). Washington, September 3-5, 1984.

Bodoff, D., & Ho, S. Y. (2016). Partial Least Squares Structural Equation Modeling Approach for Analyzing a Model with a Binary Indicator as an Endogenous Variable. available at: *Journal of the Association for Information Systems, 38*(23) http://aisel.aisnet.org/cais/vol38/iss31/23.

Bollen, K. A., & Ting, K.-F. (1998). Bootstrapping a Test Statistic for Vanishing Tetrads. *Sociological Methods & Research, 27*(1), 77–102.

Byrne, B. M., Shavelson, R. J., & Muthen, B. (1989). Testing for the Equivalence of Factor Covariance and Mean Structures: The Issue of Partial Measurement Invariance. *Psychological Bulletin, 105*(3), 456–466.

Callaghan, W., Wilson, B., Ringle, C. M., & Henseler, J. (2007). Exploring Causal Path Directionality for a Marketing Model: Using Cohen's Path Method. PLS'07: The 5th International Symposium on PLS and Related Methods, Ås, Norway.

Cantaluppi, G., & Boari, G. (2016). A Partial Least Squares Algorithm Handling Ordinal Variables. In H. Abdi, V. Esposito Vinzi, G. Russolillo, G. Saporta, & L. Trinchera (Eds.), The Multiple Facets of Partial Least Squares and Related Methods: PLS, Paris, France, 2014 (pp. 295-306). Springer International Publishing.

Capeau, F., Valette-Florence, P., & Cova, V. (2024). A Consumer Demands-resources Model of Engagement: Theoretical and Managerial Contributions from a Cross-validated Predictive Ability Test Procedure. *Journal of Business Research, 177*, Article 114619.

Carlson, J., Gudergan, S. P., Gelhard, C., & Rahman, M. M. (2019). Customer Engagement with Brands in Social Media Platforms. *European Journal of Marketing, 53*(9), 1733–1758.

Cassia, F., & Magno, F. (2024). The Value of Self-Determination Theory in Marketing Studies: Insights from the Application of PLS-SEM and NCA to Anti-food Waste Apps. *Journal of Business Research, 172*, Article 114454.

Cepeda-Carrión, G., Hair, J. F., Ringle, C. M., Roldán, J. L., & García-Fernández, J. (2022). Guest Editorial: Sports Management Research Using Partial Least Squares Structural Equation Modeling (PLS-SEM). *International Journal of Sports Marketing and Sponsorship, 23*(2), 229–240.

Cheah, J.-H., Amaro, S., & Roldán, J. L. (2023). Multigroup Analysis of More Than Two Groups in PLS-SEM: A Review, Illustration, and Recommendations. *Journal of Business Research, 156*, Article 113539.

Cheah, J.-H., Roldán, J. L., Ciavolino, E., Ting, H., & Ramayah, T. (2021). Sampling Weight Adjustments in Partial Least Squares Structural Equation Modeling: Guidelines and Illustrations. *Total Quality Management & Business Excellence, 32* (13–14), 1594–1613.

Cheah, J. H., Nitzl, C., Roldán, J. L., Cepeda Carrión, G., & Gudergan, S. P. (2021). A Primer on the Conditional Mediation Analysis in PLS-SEM. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 52*, 43–100.

Chin, W., Cheah, J.-H., Liu, Y., Ting, H., Lim, X.-J., & Cham, T. H. (2020). Demystifying the Role of Causal-predictive Modeling Using Partial Least Squares Structural Equation Modeling in Information Systems Research. *Industrial Management & Data Systems, 120*(12), 2161–2209.

Chin, W. W. (1998). The Partial Least Squares Approach to Structural Equation Modeling. In G. A. Marcoulides (Ed.), *Modern Methods for Business Research* (pp. 295–358). Lawrence Erlbaum.

Chin, W. W., & Dibbern, J. (2010). A Permutation Based Procedure for Multi-Group PLS Analysis: Results of Tests of Differences on Simulated Data and a Cross Cultural Analysis of the Sourcing of Information System Services between Germany and the USA. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of Partial Least Squares: Concepts, Methods and Applications (Springer Handbooks of Computational Statistics Series* (vol. II, pp. 171–193). Springer.

Chin, W. W., Thatcher, J. B., & Wright, R. T. (2012). Assessing Common Method Bias: Problems with the ULMC Technique. *MIS Quarterly, 36*(3), 1003–1019.

Chin, W. W., Thatcher, J. B., Wright, R. T., & Steel, D. (2013). Controlling for Common Method Variance in PLS Analysis: The Measured Latent Marker Variable Approach. In H. Abdi, W. W. Chin, V. Esposito Vinzi, G. Russolillo, & L. Trinchera (Eds.), *New Perspectives in Partial Least Squares and Related Methods* (pp. 231–239). New York: Springer.

Cho, G., Lee, J., Hwang, H., Sarstedt, M., & Ringle, C. M. (2023). A Comparative Study of the Predictive Power of Component-based Approaches to Structural Equation Modeling. *European Journal of Marketing, 57*(6), 1641–1661.

Cook, D. R., & Forzani, L. (2023). On the Role of Partial Least Squares in Path Analysis for the Social Sciences. *Journal of Business Research, 167*, Article 114132.

Dijkstra, T. K. (2014). PLS' Janus Face – Response to Professor Rigdon's 'Rethinking Partial Least Squares Modeling: In Praise of Simple Methods'. *Long Range Planning, 47*(3), 146–153.

Dijkstra, T. K., & Henseler, J. (2015). Consistent Partial Least Squares Path Modeling. *MIS Quarterly, 39*(2), 297–316.

Dijkstra, T. K., & Schermelleh-Engel, K. (2014). Consistent Partial Least Squares for Nonlinear Structural Equation Models. *Psychometrika, 79*(4), 585–604.

Dul, J. (2016). Necessary Condition Analysis (NCA): Logic and Methodology of "Necessary but not Sufficient" Causality. *Organizational Research Methods, 19*(1), 10–52.

Dul, J. (2020). *Conducting Necessary Condition Analysis*. Sage.

Esposito Vinzi, V., Trinchera, L., & Amato, S. (2010). PLS Path Modeling: From Foundations to Recent Developments and Open Issues for Model Assessment and Improvement. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of Partial Least Squares: Concepts, Methods and Applications (Springer Handbooks of Computational Statistics Series* (vol. II, pp. 47–82). Springer.

Evermann, J., & Rönkkö, M. (2023). Recent Developments in PLS. *Communications of Association for Information Systems, 52*, 663–667.

Fassott, G., Henseler, J., & Coelho, P. S. (2016). Testing moderating effects in PLS path models with composite variables. *Industrial Management & Data Systems, 116*(9), 1887–1900.

Fornell, C., Morgeson, F. V., Hult, G. T. M., & VanAmburg, D. (2020). *The Reign of the Customer: Customer-Centric Approaches to Improving Satisfaction*. Palgrave Macmilla.

Fornell, C. G., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18* (1), 39–50.

Franke, G. R., & Sarstedt, M. (2019). Heuristics versus Statistics in Discriminant Validity Testing: A Comparison of Four Procedures. *Internet Research, 29*(3), 430–447.

Gelhard, C., von Delft, S., & Gudergan, S. P. (2016). Heterogeneity in Dynamic Capability Configurations: Equifinality and Strategic Performance. *Journal of Business Research, 69*(11), 5272–5279.

Grimm, M. S., & Wagner, R. (2020). The Impact of Missing Values on PLS, ML and FIML Model Fit. *Archives of Data Science, Series A, 6*(1), 1–17.

Gudergan, S. P., Ringle, C. M., Wende, S., & Will, A. (2008). Confirmatory Tetrad Analysis in PLS Path Modeling. *Journal of Business Research, 61*(12), 1238–1249.

Guenther, P., Guenther, M., Ringle, C. M., Zaefarian, G., & Cartwright, S. (2023). Improving PLS-SEM Use for Business Marketing Research. *Industrial Marketing Management, 111*(May), 127–142.

Hahn, C., Johnson, M. D., Herrmann, A., & Huber, F. (2002). Capturing Customer Heterogeneity Using a Finite Mixture PLS Approach. *Schmalenbach Business Review, 54*(3), 243–269.

Hair, J. F. (2021). Next Generation Prediction Metrics for Composite-based PLS-SEM. *Industrial Management & Data Systems, 121*(1), 5–11.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019a). Multivariate Data Analysis (8 ed.). Cengage Learning.

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing Measurement Model Quality in PLS-SEM Using Confirmatory Composite Analysis. *Journal of Business Research, 109*, 101–110.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* ((3 ed.).). Sage.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R*. Springer.

Hair, J. F., Ringle, C. M., Gudergan, S. P., Fischer, A., Nitzl, C., & Menictas, C. (2019b). Partial Least Squares Structural Equation Modeling-based Discrete Choice Modeling: An Illustration in Modeling Retailer Choice. *Business Research, 12*, 115–140.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. *Journal of Marketing Theory and Practice, 19*(2), 139–151.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019c). When to Use and How to Report the Results of PLS-SEM. *European Business Review, 31*(1), 2–24.

Hair, J. F., & Sarstedt, M. (2021). Explanation Plus Prediction: The Logical Focus of Project Management Research. *Project Management Journal, 52*(4), 319–322.

Hair, J. F., Sarstedt, M., Matthews, L., & Ringle, C. M. (2016). Identifying and Treating Unobserved Heterogeneity with FIMIX-PLS: Part I - Method. *European Business Review, 28*(1), 63–76.

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019d). Rethinking Some of the Rethinking of Partial Least Squares. *European Journal of Marketing, 53*(4), 566–584.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2024c). *Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2 ed.). Sage.

Hair, J. F., Sarstedt, M., Ringle, C. M., Sharma, P. N., & Liengaard, B. D. (2024a). Going Beyond the Untold Facts in PLS-SEM and Moving Forward. *European Journal of Marketing, 58*(13), 81–106.

Hair, J. F., Sarstedt, M., Ringle, C. M., Sharma, P. N., & Liengaard, B. D. (2024b). The Shortcomings of Equal Weights Estimation and the Composite Equivalence Index in PLS-SEM. *European Journal of Marketing, 58*(13), 30–55.

Hauff, S., Richter, N. F., Sarstedt, M., & Ringle, C. M. (2024). Importance and Performance in PLS-SEM and NCA: Introducing the Combined Importance-Performance Map Analysis (cIPMA). *Journal of Retailing and Consumer Services, 78*, Article 103723.

Hayes, A. F. (2022). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach* ((3 ed.).). Guilford Press.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., Ketchen, D. J., Hair, J. F., Hult, G. T. M., & Calantone, R. J. (2014). Common Beliefs and Reality about Partial Least Squares: Comments on Rönkkö & Evermann (2013). *Organizational Research Methods, 17*(2), 182–209.

Henseler, J., & Fassott, G. (2010). Testing Moderating Effects in PLS Path Models: An Illustration of Available Procedures. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of Partial Least Squares: Concepts, Methods and Applications (Springer Handbooks of Computational Statistics Series* (vol. II, pp. 713–735). Springer.

Henseler, J., Hubona, G. S., & Ray, P. A. (2016a). Using PLS Path Modeling in New Technology Research: Updated Guidelines. *Industrial Management & Data Systems, 116*(1), 1–19.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A New Criterion for Assessing Discriminant Validity in Variance-based Structural Equation Modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2016b). Testing Measurement Invariance of Composites Using Partial Least Squares. *International Marketing Review, 33*(3), 405–431.

Henseler, J., & Sarstedt, M. (2013). Goodness-of-Fit Indices for Partial Least Squares Path Modeling. *Computational Statistics, 28*(2), 565–580.

Henseler, J., & Schuberth, F. (2020). Using Confirmatory Composite Analysis to Assess Emergent Variables in Business Research. *Journal of Business Research, 120*, 147–156.

Höck, C., Ringle, C. M., & Sarstedt, M. (2010). Management of Multi-Purpose Stadiums: Importance and Performance Measurement of Service Interfaces. *International Journal of Services Technology and Management, 14*(2/3), 188–207.

Hofman, J. M., Sharma, A., & Watts, D. J. (2017). Prediction and Explanation in Social Systems. *Science, 355*(6324), 486–488.

Hofman, J. M., Watts, D. J., Athey, S., Garip, F., Griffiths, T. L., Kleinberg, J., Margetts, H., Mullainathan, S., Salganik, M. J., Vazire, S., Vespignani, A., & Yarkoni, T. (2021). Integrating Explanation and Prediction in Computational Social Science. *Nature, 595*(7866), 181–188.

Huang, W. (2013). *PLSe: Efficient Estimators and Tests for Partial Least Square (Dissertation)*. University of California Los Angeles.

Hult, G. T. M., Hair, J. F., Proksch, D., Sarstedt, M., Pinkwart, A., & Ringle, C. M. (2018). Addressing Endogeneity in International Marketing Applications of Partial Least Squares Structural Equation Modeling. *Journal of International Marketing, 26*(3), 1–21.

Hwang, H., & Cho, G. (2020). Global Least Squares Path Modeling: A Full-Information Alternative to Partial Least Squares Path Modeling. *Psychometrika, 85*(4), 947–972.

Hwang, H., Sarstedt, M., Cheah, J. H., & Ringle, C. M. (2020). A Concept Analysis of Methodological Research on Composite-based Structural Equation Modeling: Bridging PLSPM and GSCA. *Behaviormetrika, 47*, 219–241.

Hwang, H., & Takane, Y. (2004). Generalized Structured Component Analysis. *Psychometrika, 69*(1), 81–99.

Hwang, H., & Takane, Y. (2014). *Generalized Structured Component Analysis: A Component-Based Approach to Structural Equation Modeling*. Chapman & Hall.

Jakobowicz, E., & Derquenne, C. (2007). A Modified PLS Path Modeling Algorithm Handling Reflective Categorical Variables and a New Model Building Strategy. *Computational Statistics & Data Analysis, 51*(8), 3666–3678.

Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research. *Journal of Consumer Research, 30*(2), 199–218.

Jedidi, K., Jagpal, H. S., & DeSarbo, W. S. (1997). Finite-Mixture Structural Equation Models for Response-Based Segmentation and Unobserved Heterogeneity. *Marketing Science, 16*(1), 39–59.

Ji, E., Mahmudur Rahman, S., Wilden, R., Lin, N., & Harrison, N. (2024). Leveraging Customer Knowledge Obtained Through Social Media: The Roles of R&D Intensity and Absorptive Capacity. *Journal of Business Research, 182*, Article 114811.

Jöreskog, K. G., & Wold, H. (1982). The ML and PLS Techniques for Modeling with Latent Variables: Historical and Comparative Aspects. In K. G. Jöreskog, & H. Wold (Eds.), *Systems Under Indirect Observation, Part I* (pp. 263–270). North-Holland.

Klarmann, M., & Feurer, S. (2018). Control Variables in Marketing Research. *Marketing: ZFP – Journal of Research and Management, 40*(2), 26–40.

Klesel, M., Schuberth, F., Niehaves, B., & Henseler, J. (2022). Multigroup Analysis in Information Systems Research using PLS-PM: A Systematic Investigation of Approaches. *SIGMIS Database, 53*(3), 26–48.

Kock, N. (2015). Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach. *International Journal of e-Collaboration, 11*(4), 1–10.

Kurtaliqi, F., Lancelot Miltgen, C., Viglia, G., & Pantin-Sohier, G. (2024). Using Advanced Mixed Methods Approaches: Combining PLS-SEM and Qualitative Studies. *Journal of Business Research, 172*, Article 114464.

Legate, A. E., Hair, J. F., Chretien, J. L., & Risher, J. J. (2023). PLS-SEM: Prediction-oriented Solutions for HRD Researchers. *Human Resource Development Quarterly, 34*(1), 91–109.

Liengaard, B., Becker, J.-M., Bennedsen, M., Heiler, P., Taylor, L. N., & Ringle, C. M. (2024). Dealing with Regression Models' Endogeneity by Means of an Adjusted Estimator for the Gaussian Copula approach. *Journal of the Academy of Marketing Science*. Advance online publication.

Liengaard, B. D. (2024). Measurement Invariance Testing in Partial Least Squares Structural Equation Modeling. *Journal of Business Research, 177*, Article 114581.

Liengaard, B. D., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: Coveted, Yet Forsaken? Introducing a Cross-validated Predictive Ability Test in Partial Least Squares Path Modeling. *Decision Sciences, 52*(2), 362–392.

Lohmöller, J.-B. (1989). Latent Variable Path Modeling with Partial Least Squares. *Physica*.

Mansoor, M., Paul, J., Saeed, A., & Cheah, J.-H. (2024). When Mass Meets Prestige: The Impact of Symbolic Motivations, Inspirations, and Purchase Intentions for Masstige Products. *Journal of Business Research, 176*, Article 114591.

Manzi-Puertas, M. A., Agirre-Aramburu, I., & López-Pérez, S. (2024). Navigating the Student Entrepreneurial Journey: Dynamics and Interplay of Resourceful and Innovative Behavior. *Journal of Business Research, 174*, Article 114524.

Marcoulides, G. A., Chin, W. W., & Saunders, C. (2012). When Imprecise Statistical Statements Become Problematic: A Response to Goodhue, Lewis, and Thompson. *MIS Quarterly, 36*(3), 717–728.

Marcoulides, G. A., & Drezner, Z. (2001). Specification Searches in Structural Equation Modeling with a Genetic Algorithm. In G. A. Marcoulides, & R. E. Schumacker (Eds.), *Advanced Structural Equation Modeling: New Developments and Techniques* (pp. 247–268). Lawrence Erlbaum.

Marcoulides, G. A., & Drezner, Z. (2003). Model Specification Searches Using Ant Colony Optimization Algorithms. *Structural Equation Modeling, 10*(1), 154–164.

Marcoulides, G. A., Drezner, Z., & Schumacker, R. E. (1998). Model Specification Searches in Structural Equation Modeling Using Tabu Search. *Structural Equation Modeling: A Multidisciplinary Journal, 5*(4), 365–376.

Marcoulides, G. A., & Saunders, C. (2006). PLS: A Silver Bullet? *MIS Quarterly, 30*(2).

Martensen, A., & Grønholdt, L. (2003). Improving Library Users' Perceived Quality, Satisfaction and Loyalty: An Integrated Measurement and Management System. *The Journal of Academic Librarianship, 29*(3), 140–147.

Martilla, J. A., & James, J. C. (1977). Importance-Performance Analysis. *Journal of Marketing, 41*(1), 77–79.

Matthews, L. (2017). Applying Multi-Group Analysis in PLS-SEM: A Step-by-Step Process. In H. Latan, & R. Noonan (Eds.), *Partial Least Squares Structural Equation Modeling: Basic Concepts, Methodological Issues and Applications* (pp. 219–243). Springer.

Matthews, L., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2016). Identifying and Treating Unobserved Heterogeneity with FIMIX-PLS: Part II – A Case Study. *European Business Review, 28*(2), 208–224.

McDonald, R. P. (1996). Path Analysis with Composite Variables. *Multivariate Behavioral Research, 31*(2), 239–270.

Memon, M. A., Cheah, J.-H., Ramayah, T., Ting, H., & Chuah, F. (2018). Mediation Analysis: Issues and Recommendations. *Journal of Applied Structural Equation Modeling, 2*(1), i–ix.

Memon, M. A., Cheah, J.-H., Ramayah, T., Ting, H., Chuah, F., & Cham, T. H. (2019). Moderation Analysis: Issues and Guidelines. *Journal of Applied Structural Equation Modeling, 3*(1), i–ix.

Millsap, R. E. (2011). *Statistical Approaches to Measurement Invariance*. Routledge.

Mkedder, N., & Bakır, M. (2023). A Hybrid Analysis of Consumer Preference for Domestic Products: Combining PLS-SEM and ANN Approaches. *Journal of Global Marketing, 36*(5), 372–395.

Morgeson, F. V., Hult, G. T. M., Sharma, U., & Fornell, C. (2023). The American Customer Satisfaction Index (ACSI): A Sample Dataset and Description. *Data in Brief, 48*, Article 109123.

Nitzl, C., Roldán, J. L., & Cepeda Carrión, G. (2016). Mediation Analysis in Partial Least Squares Path Modeling: Helping Researchers Discuss More Sophisticated Models. *Industrial Management & Data Systems, 116*(9), 1849–1864.

Pace, V. L. (2009). Method Variance From the Perspectives of Reviewers: Poorly Understood Problem or Overemphasized Complaint? *Organizational Research Methods, 13*(3), 421–434.

Park, S., & Gupta, S. (2012). Handling Endogenous Regressors by Joint Estimation Using Copulas. *Marketing Science, 31*(4), 567–586.

Petter, S. (2018). "Haters Gonna Hate": PLS and Information Systems Research. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems, 49*(2), 10–13.

Petter, S., & Hadavi, Y. (2021). With Great Power Comes Great Responsibility: The Use of Partial Least Squares in Information Systems Research. ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 52(SI), 10-23.

Petter, S., & Hadavi, Y. (2023). Use of Partial Least Squares Path Modeling Within and Across Business Disciplines. In H. Latan, J. F. Hair, & R. Noonan (Eds.), *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications* (pp. 55–79). Springer International Publishing.

Picón Berjoyo, A., Ruiz-Moreno, C., & Castro, I. (2016). A Mediating and Multigroup Analysis of Customer Loyalty. *European Management Journal*. in press.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *Journal of Applied Psychology, 88*(5), 879–903.

Qureshi, I., & Compeau, D. R. (2009). Assessing Between-Group Differences in Information Systems Research: A Comparision of Covariance- and Component-Based SEM. *MIS Quarterly, 33*(1), 197–214.

Radomir, L., Ciornea, R., Wang, H., Liu, Y., Ringle, C. M., & Sarstedt, M. (Eds.). (2023). State of the Art in Partial Least Squares Structural Equation Modeling (PLS-SEM): Methodological Extensions and Applications in the Social Sciences and Beyond. Springer.

Rasoolimanesh, S. M., Ringle, C. M., Sarstedt, M., & Olya, H. (2021). The Combined Use of Symmetric and Asymmetric Approaches: Partial Least Squares-structural Equation Modeling and Fuzzy-set Qualitative Comparative Analysis. *International Journal of Contemporary Hospitality Management, 33*(5), 1571–1592.

Richter, N. F., Hauff, S., Ringle, C. M., Sarstedt, M., Kolev, A. E., & Schubring, S. (2023). How to Apply Necessary Condition Analysis in PLS-SEM. In H. Latan, J. F. Hair, & R. Noonan (Eds.), *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications* (pp. 267–297). Springer International Publishing.

Richter, N. F., Schubring, S., Hauff, S., Ringle, C. M., & Sarstedt, M. (2020). When Predictors of Outcomes are Necessary: Guidelines for the Combined Use of PLS-SEM and NCA. *Industrial Management & Data Systems, 120*(12), 2243–2267.

Richter, N. F., & Tudoran, A. A. (2024). Elevating Theoretical Insight and Predictive Accuracy in Business Research: Combining PLS-SEM and Selected Machine Learning Algorithms. *Journal of Business Research, 173*, Article 114453.

Rigdon, E. E. (2012). Rethinking Partial Least Squares Path Modeling: In Praise of Simple Methods. *Long Range Planning, 45*(5–6), 341–358.

Rigdon, E. E. (2016). Choosing PLS Path Modeling as Analytical Method in European Management Research: A Realist Perspective. *European Management Journal, 34*(6), 598–605.

Rigdon, E. E. (2023). Needed Developments in the Understanding of Quasi Factor Methods. *Communications of the Association for Information Systems, 52*, 692–696.

Rigdon, E. E., Ringle, C. M., & Sarstedt, M. (2010). Structural Modeling of Heterogeneous Data with Partial Least Squares. In N. K. Malhotra (Ed.), Review of marketing research (Vol. 7, pp. 255-296). Sharpe.

Rigdon, E. E., Sarstedt, M., & Ringle, C. M. (2017). On Comparing Results from CB-SEM and PLS-SEM. *Five Perspectives and Five Recommendations. Marketing ZFP, 39*(3), 4–16.

Riggs, R., Felipe, C. M., Roldán, J. L., & Real, J. C. (2024). Information Systems Capabilities Value Creation Through Circular Economy Practices in Uncertain Environments: A Conditional Mediation Model. *Journal of Business Research, 175*, Article 114526.

Ringle, C. M., Sarstedt, M., & Schlittgen, R. (2010). Finite Mixture and Genetic Algorithm Segmentation in Partial Least Squares Path Modeling: Identification of Multiple Segments in a Complex Path Model. In A. Fink, B. Lausen, W. Seidel, & A. Ultsch (Eds.), *Advances in Data Analysis, Data Handling and Business Intelligence* (pp. 167–176). Springer.

Ringle, C. M., Sarstedt, M., & Schlittgen, R. (2014a). Genetic Algorithm Segmentation in Partial Least Squares Structural Equation Modeling. *OR Spectrum, 36*(1), 251–276.

Ringle, C. M., Sarstedt, M., & Schlittgen, R. (2014b). Genetic Algorithm Segmentation in Partial Least Squares Structural Equation Modeling: Online Appendix. *OR Spectrum, 36*(1), 251–276.

Ringle, C. M., Sarstedt, M., Sinkovics, N., & Sinkovics, R. R. (2023). A Perspective on Using Partial Least Squares Structural Equation Modelling in Data Articles. *Data in Brief, 48*, Article 109074.

Ringle, C. M., Sarstedt, M., & Straub, D. W. (2012). A Critical Look at the Use of PLS-SEM in MIS Quarterly. *MIS Quarterly, 36*(1), iii–xiv.

Ringle, C. M., Wende, S., & Becker, J.-M. (2024). SmartPLS 4. *SmartPLS GmbH*. https://www.smartpls.com/.

Roemer, E. (2016). A Tutorial on the Use of PLS Path Modeling in Longitudinal Studies. *Industrial Management & Data Systems, 116*(9), 1901–1921.

Rönkkö, M., & Evermann, J. (2013). A Critical Examination of Common Beliefs About Partial Least Squares Path Modeling. *Organizational Research Methods, 16*(3), 425–448.

Rönkkö, M., Lee, N., Evermann, J., McIntosh, C. N., & Antonakis, J. (2023). Marketing or Methodology? Exposing Fallacies of PLS with Simple Demonstrations. *European Journal of Marketing, 57*(6), 1597–1617.

Rönkkö, M., McIntosh, C. N., & Aguirre-Urreta, M. I. (2016). Improvements to PLSc: Remaining Problems and Simple Solutions Aalto University. https://aaltodoc.aalto.fi/bitstream/handle/123456789/19844/J_r%F6nkk%F6_mikko_2016.pdf?sequence=4.

Rönkkö, M., McIntosh, C. N., & Antonakis, J. (2015). On the Adoption of Partial Least Squares in Psychological Research: Caveat Emptor. *Personality and Individual Differences, 87*, 76–84.

Rossi, P. E. (2014). Even the Rich Can Make Themselves Poor: A Critical Examination of IV Methods in Marketing Applications. *Marketing Science, 33*(5), 655–672.

Russo, D., & Stol, K.-J. (2023). Don't Throw the Baby Out With the Bathwater: Comments on "Recent Developments in PLS". *Communications of the Association for Information Systems, 52*, 700–704.

Russolillo, G. (2012). Non-Metric Partial Least Squares. *Electronic Journal of Statistics, 6*, 1641–1669.

Sande, J. B., & Ghosh, M. (2018). Endogeneity in Survey Research. *International Journal of Research in Marketing, 35*(2), 185–204.

Sarstedt, M., Adler, S. J., Ringle, C. M., Cho, G., Diamantopoulos, A., Hwang, H., & Liengaard, B. D. (2024a). Same Model, Same Data, But Different Outcomes: Evaluating the Impact of Method Choices in Structural Equation Modeling. *Journal of Product Innovation Management, 41*(6), 1100–1117.

Sarstedt, M., Becker, J.-M., Ringle, C. M., & Schwaiger, M. (2011a). Uncovering and Treating Unobserved Heterogeneity with FIMIX-PLS: Which Model Selection Criterion Provides an Appropriate Number of Segments? *Schmalenbach Business Review, 63*(1), 34–62.

Sarstedt, M., Bengart, P., Shaltoni, A. M., & Lehmann, S. (2018). The Use of Sampling Methods in Advertising Research: A Gap Between Theory and Practice. *International Journal of Advertising, 37*(4), 650–663.

Sarstedt, M., & Danks, N. P. (2022). Prediction in HRM Research: A Gap Between Rhetoric and Reality. *Human Resource Management Journal, 32*(2), 485–513.

Sarstedt, M., Hair, J. F., Cheah, J.-H., Becker, J.-M., & Ringle, C. M. (2019). How to Specify, Estimate, and Validate Higher-order Constructs in PLS-SEM. *Australasian Marketing Journal, 27*(3), 197–211.

Sarstedt, M., Hair, J. F., Nitzl, C., Ringle, C. M., & Howard, M. C. (2020). Beyond a Tandem Analysis of SEM and PROCESS: Use of PLS-SEM for Mediation Analyses! *International Journal of Market Research, 62*(3), 288–299.

Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022a). Progress in Partial Least Squares Structural Equation Modeling Use in Marketing Research in the Last Decade. *Psychology & Marketing, 39*(5), 1035–1064.

Sarstedt, M., Hair, J. F., & Ringle, C. M. (2022b). "PLS-SEM: indeed a silver bullet" – retrospective observations and recent advances. *Journal of Marketing Theory & Practice, 31*(3), 261–275. Advance online publication.

Sarstedt, M., Hair, J. F., & Ringle, C. M. (2023a). "PLS-SEM: Indeed a Silver Bullet" – Retrospective Observations and Recent Advances. *Journal of Marketing Theory & Practice, 31*(3), 261–275.

Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation Issues with PLS and CBSEM: Where the Bias Lies! *Journal of Business Research, 69*(10), 3998–4010.

Sarstedt, M., Henseler, J., & Ringle, C. M. (2011b). Multi-Group Analysis in Partial Least Squares (PLS) Path Modeling: Alternative Methods and Empirical Results. In M. Sarstedt, M. Schwaiger, & C. R. Taylor (Eds.), Advances in International Marketing, Volume 22 (Vol. 22, pp. 195-218). Emerald.

Sarstedt, M., Radomir, L., Moisescu, O. I., & Ringle, C. M. (2022). Latent Class Analysis in PLS-SEM: A Review and Recommendations for Future Applications. *Journal of Business Research, 138*, 398–407.

Sarstedt, M., Richter, N. F., Hauff, S., & Ringle, C. M. (2024b). Combined Importance–performance Map Analysis (cIPMA) in Partial Least Squares Structural Equation Modeling (PLS–SEM): A SmartPLS 4 Tutorial. *Journal of Marketing Analytics*. Advance online publication.

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Treating Unobserved Heterogeneity in PLS-SEM: A Multi-Method Approach. In R. Noonan, & H. Latan (Eds.), *Partial Least Squares Structural Equation Modeling: Basic Concepts, Methodological Issues and Applications* (pp. 197–217). Springer.

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial Least Squares Structural Equation Modeling. In C. Homburg, M. Klarmann, & A. E. Vomberg (Eds.), *Handbook of Market Research* (pp. 1–47). Springer.

Sarstedt, M., Ringle, C. M., & Iuklanov, D. (2023b). Antecedents and Consequences of Corporate Reputation: A Dataset. *Data in Brief, 48*, Article 109079.

Schlittgen, R., Ringle, C. M., Sarstedt, M., & Becker, J.-M. (2016). Segmentation of PLS Path Models by Iterative Reweighted Regressions. *Journal of Business Research, 69*(10), 4583–4592.

Schuberth, F., Henseler, J., & Dijkstra, T. K. (2018a). Confirmatory Composite Analysis [Methods]. *Frontiers in Psychology, 9*(2541).

Schuberth, F., Henseler, J., & Dijkstra, T. K. (2018b). Partial Least Squares Path Modeling Using Ordinal Categorical Indicators. *Quality & Quantity, 52*(1), 9–35.

Schuberth, F., Rademaker, M. E., & Henseler, J. (2023). Assessing the Overall Fit of Composite Models Estimated by Partial Least Squares Path Modeling. *European Journal of Marketing, 57*(6), 1678–1702.

Schubring, S., Lorscheid, I., Meyer, M., & Ringle, C. M. (2016). The PLS Agent: Predictive Modeling with PLS-SEM and Agent-based Simulation. *Journal of Business Research, 69*(10), 4604–4612.

Schwaiger, M. (2004). Components and Parameters of Corporate Reputation: An Empirical Study. *Schmalenbach Business Review, 56*(1), 46–71.

Schwaiger, M., Sarstedt, M., & Taylor, C. R. (2010). Art for the Sake of the Corporation: Audi, BMW Group, DaimlerChrysler, Montblanc, Siemens, and Volkswagen Help Explore the Effect of Sponsorship on Corporate Reputations. *Journal of Advertising Research, 50*(1), 77–90.

Schwarz, G. (1978). Estimating the Dimensions of a Model. *Annals of Statistics, 6*(2), 461–464.

Sharma, P. N., Liengaard, B. D., Hair, J. F., Sarstedt, M., & Ringle, C. M. (2023a). Predictive Model Assessment and Selection in Composite-based Modeling Using PLS-SEM: Extensions and Guidelines for Using CVPAT. *European Journal of Marketing, 57*(6), 1662–1677.

Sharma, P. N., Liengaard, B. D., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2023b). Extraordinary Claims Require Extraordinary Evidence: A Comment on "the Recent Developments in PLS". *Communications of the Association for Information Systems, 52*, 739–742.

Sharma, P. N., Sarstedt, M., Ringle, C. M., Cheah, J.-H., Herfurth, A., & Hair, J. F. (2024). A Framework for Enhancing the Replicability of Behavioral MIS Research Using Prediction Oriented Techniques. *International Journal of Information Management, 78*, Article 102805.

Shela, V., Danks, N. P., Ramayah, T., & Ahmad, N. H. (2024). An Application of the COA Framework: Building a Sound Foundation for Organizational Resilience. *Journal of Business Research, 179*, Article 114702.

Shmueli, G. (2010). To Explain or to Predict? *Statistical Science, 25*(3), 289–310.

Shmueli, G., & Koppius, O. R. (2011). Predictive Analytics in Information Systems Research. *MIS Quarterly, 35*(3), 553–572.

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The Elephant in the Room: Evaluating the Predictive Performance of PLS Models. *Journal of Business Research, 69*(10), 4552–4564.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive Model Assessment in PLS-SEM: Guidelines for Using PLSpredict. *European Journal of Marketing, 53*(11), 2322–2347.

Slack, N. (1994). The Importance-Performance Matrix as a Determinant of Improvement Priority. *International Journal of Operations and Production Management, 44*(5), 59–75.

Spector, P. E. (2006). Method Variance in Organizational Research: Truth or Urban Legend? *Organizational Research Methods, 9*(2), 221–232.

Spector, P. E., & Brannick, M. T. (2010). Common Method Issues: An Introduction to the Feature Topic in Organizational Research Methods. *Organizational Research Methods, 13*(3), 403–406.

Tenenhaus, M., Esposito Vinzi, V., Chatelin, Y.-M., & Lauro, C. (2005). PLS Path Modeling. *Computational Statistics & Data Analysis, 48*(1), 159–205.

Troiville, J. (2024). Connecting the Dots Between Brand Equity and Brand Loyalty for Retailers: The Mediating Roles of Brand Attitudes and Word-of-Mouth Communication. *Journal of Business Research, 177*, Article 114650.

Vaithilingam, S., Ong, C. S., Moisescu, O. I., & Nair, M. S. (2024). Robustness Checks in PLS-SEM: A Review of Recent Practices and Recommendations for Future Applications in Business Research. *Journal of Business Research, 173*, Article 114465.

Vandenberg, R. J., & Lance, C. E. (2000). A Review and Synthesis of the Measurement Invariance Literature: Suggestions, Practices, and Recommendations for Organizational Research. *Organizational Research Methods, 3*(1), 4–70.

Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant Validity Testing in Marketing: An Analysis, Causes for Concern, and Proposed Remedies. *Journal of the Academy of Marketing Science, 44*(1), 119–134.

Wang, H., Lu, S., & Liu, Y. (2022). Missing Data Imputation in PLS-SEM. *Quality & Quantity, 56*(6), 4777–4795.

Wetzels, M., Odekerken-Schroder, G., & van Oppen, C. (2009). Using PLS Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustration. *MIS Quarterly, 33*(1), 177–195.

Wold, H. (1973). Nonlinear Iterative Partial Least Squares (NIPALS) Modelling: Some Current Developments. Proceedings of the 3rd International Symposium on Multivariate Analysis, Dayton, OH.

Wold, H. (1975). Path Models with Latent Variables: The NIPALS Approach. In H. M. Blalock, A. Aganbegian, F. M. Borodkin, R. Boudon, & V. Capecchi (Eds.), *Quantitative Sociology: International Perspectives on Mathematical and Statistical Modeling* (pp. 307–357). Academic Press.

Wold, H. (1982). Soft Modeling: The Basic Design and Some Extensions. In K. G. Jöreskog, & H. Wold (Eds.), *Systems Under Indirect Observations: Part II* (pp. 1–54). North-Holland.

Wold, H. (1985). Partial Least Squares. In S. Kotz, & N. L. Johnson (Eds.), *Encyclopedia of Statistical Sciences* (Vol. 6, pp. 581–591). Wiley.

Wold, H., & Lyttkens, E. (1969). Nonlinear Iterative Partial Least Squares (NIPALS) Estimation Procedures. *Bulletin of the International Statistical Institute, 43*, 29–51.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* ((2 ed.).). MIT Press.

Yuan, K.-H. (2023). Comments on the Article "Marketing or Methodology? Exposing the Fallacies of PLS with Simple Demonstrations" and PLS-SEM in General. *European Journal of Marketing, 57*(6), 1618–1625.

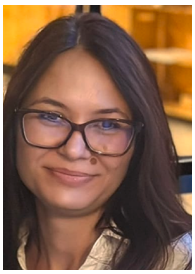
Yuan, K.-H., Wen, Y., & Tang, J. (2020). Regression Analysis with Latent Variables by Partial Least Squares and Four Other Composite Scores: Consistency, Bias and Correction. *Structural Equation Modeling: A Multidisciplinary Journal, 27*(3), 333–350.

Zaefarian, G., Kadile, V., Henneberg, S. C., & Leischnig, A. (2017). Endogeneity Bias in Marketing Research: Problem, Causes and Remedies. *Industrial Marketing Management, 65*, 39–46.

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *Journal of Consumer Research, 37*(3), 197–206.

Siegfried P. Gudergan is a Professor of Strategy at James Cook University in Australia. He also is a Visiting Distinguished Professor at Aalto University in Finland, Visiting Professor at Vienna University of Economics and Business (WU Wien) in Austria, and Emeritus Professor at the University of Waikato in New Zealand. His research in marketing and management as well as quantitative methods has been published in leading management, strategy, tourism and marketing journals.

Ovidiu I. Moisescu is Professor of Marketing and Branding at the Marketing Department, Faculty of Economics and Business Administration at Babeș-Bolyai University of Cluj-Napoca, Romania. He completed his PhD in Marketing at the West University of Timișoara (Romania), as well as a postdoctoral research project at Babeș-Bolyai University of Cluj-Napoca (Romania) and Corvinus University of Budapest (Hungary). His research focuses on consumer behavior, brand loyalty, CSR, and methodological issues in PLS-SEM.



Lăcrămioara Radomir is a Lecturer in the Department of Marketing, Faculty of Economics and Business Administration, Babeș-Bolyai University, Cluj-Napoca, Romania. Her research interests relate to service marketing, relationship quality, corporate reputation, employer attractiveness, and methodological issues in PLS-SEM. She holds a PhD in Marketing from Babeș-Bolyai University and is the recipient of a postdoctoral scholarship cofounded by the European Union.

Christian M. Ringle is a Chaired Professor of Management and Decision Sciences at the Hamburg University of Technology (Germany), an Adjunct Research Professor at the James Cook University (Australia) and a Visiting Scholar at the University of California, Berkeley (USA). His research interests are in the areas of management and marketing, method development, business analytics, machine learning, and the application of business research methods to management decision-making. Since 2018, Christian has been included in the list of Highly Researchers by Clarivate Analytics. He is a co-founder and co-developer of the statistical software SmartPLS (https://www.smartpls.com). More information: https://www.tuhh.de/mds/team/prof-dr-c-m-ringle.

Marko Sarstedt is a Chaired Professor of Marketing at the Ludwig-Maximilians-University Munich (Germany) and an Adjunct Research Professor at Babeș-Bolyai-University Cluj-Napoca (Romania). His main research interest is the advancement of research methods to further the understanding of consumer behavior. His research has been published in *Nature Human Behavior*, *Journal of Marketing Research*, *Journal of the Academy of Marketing Science*, *Multivariate Behavioral Research*, *Organizational Research Methods*, *MIS Quarterly*, and *Psychometrika*, among others. Marko has been repeatedly named member of Clarivate Analytics' Highly Cited Researchers List, which includes the "world's most impactful scientific researchers."