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

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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

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[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).

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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)

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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 $PLS_{predict}$ 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)

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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)

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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.

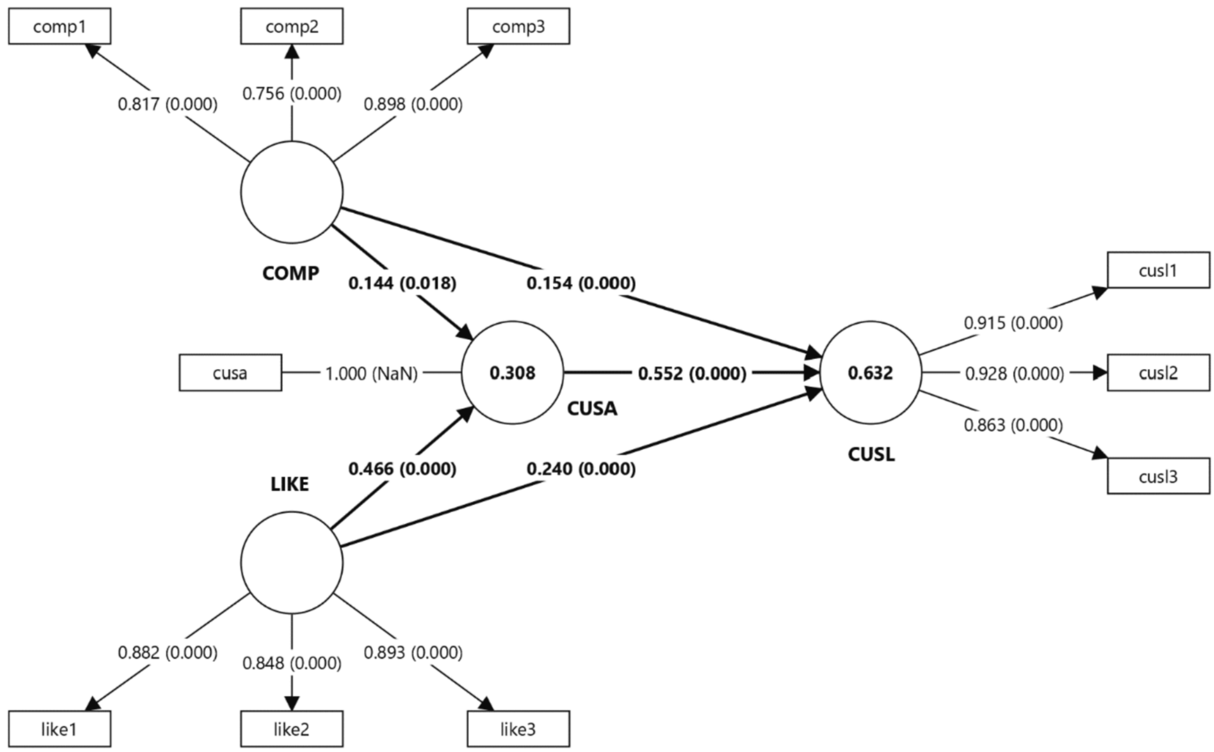

Fig. 1. PLS-SEM results for the simple corporate reputation example. Note: circles = constructs; rectangles = indicators; values on the path relationships = standardized coefficients with bootstrap p values in brackets; values in the circles = R^2 values.

- 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.

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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.

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Data availability

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

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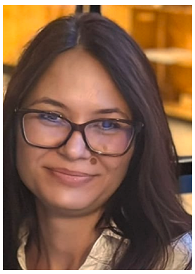

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