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EDITORIAL

Advanced marketing analytics using partial least squares structural equation modeling (PLS-SEM)

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The use of partial least squares structural equation modeling (PLS-SEM) as a means to analyze complex interrelationships between latent variables and their indicators (Hair et al. 2022; Lohmöller 1989; Wold 2005) has recently surged—not only in fields that popularized the method such as management information systems, marketing, and strategic management (e.g., Guenther et al. 2023; Hair et al. 2017; Sarstedt et al. 2022), but in various other disciplines such as agriculture, engineering, environmental sciences and ecology, geography, and psychology. PLS-SEM's methodological features have clearly extended researchers' capacities to better understand the complex interrelationships that constitute the "black box" of a variety of attitudinal and behavioral theories as well as explain and predict unobservable phenomena (e.g., Petter 2018; Petter and Hadavi 2021; Russo and Stol 2022). For example, articles recently published in *Journal of Marketing Analytics* have used PLS-SEM to assess the effects of COVID-19-related risk on online shopping behavior (Soares et al. 2023), the influence of storytelling on the consumer-brand relationship experience (Crespo et al. 2023), and the drivers of consumer trust in live streaming platforms (Leong et al. 2023). Many of these studies rely on advanced modeling and model assessment routines, which have been developed over the last years (Hair et al. 2024). Examples include (1) the analysis of complex model relationships involving nonlinear effects (Basco et al. 2022), conditional mediating effects (Cheah et al. 2021), or higher-order models (Sarstedt et al. 2019), (2) the use of model evaluation routines for discriminant validity (Ringle et al. 2023), predictive power (Shmueli et al. 2016), or endogeneity assessment (Becker et al. 2022), and (3) the combined use of PLS-SEM with methods from machine learning (Sternad Zabukovšek et al. 2022), or other fields (e.g., Richter et al. 2020). This special issue brings together high-quality papers that apply or advance these state-of-the-art extensions of the original PLS-SEM method, several of which were presented at the *2022 International Conference on Partial Least Squares Structural Equation Modeling*, held in September 6–9, 2022 at the *Faculty of Economics and Business Administration* of the *Babeș-Bolyai University*, Cluj-Napoca, Romania.

The first two papers presented in this special issue introduce a new dimension to the analysis and interpretation of PLS-SEM results, which inherently follows a sufficiency logic. According to this logic, the parameter estimates express the strength of the relationships between model elements, most notably the constructs of interest. This is reflected in authors' interpretation of the results who typically use expressions such as "we find that attractiveness (…) and performance (…) have a particularly strong effect on the cognitive corporate reputation construct, while attractiveness (…) and quality (…) are the most important explanators for the affective corporate reputation dimension" (Damberg et al. 2022, p. 9). While such findings are highly relevant for managerial practice, they imply that the absence of a certain determinant such as attractiveness in Damberg et al.'s 2022 analysis can, in principle, be compensated by other determinants such as performance or quality. However, intuition tells us that this is rarely the case.

Addressing this concern, Dul (2016a, b) proposed the necessary condition analysis (NCA), which assumes that an outcome—or a certain level of an outcome—can only be achieved if the necessary cause is in place or is at a certain level. Following this necessity logic, researchers may, for example, conclude that achieving a certain level of reputation requires an attractiveness-level of 60%. The practical benefits of such conclusions are obvious as they offer

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concrete managerial guidance as to which effort is needed to produce a desired outcome. Not surprisingly, the NCA has recently attracted considerable attention (Dul et al. 2023) and has also gained prominence as a means to enrich PLS-SEM analyses. To derive necessary conditions, researchers applying PLS-SEM use the construct scores after algorithm convergence as input for an NCA (Richter et al. 2020, 2022, 2023). The construct scores of the determinants and the outcome are then contrasted in separate scatterplots which include ceiling lines that characterize the maximum input–output relations (i.e., the highest possible outcome that can be achieved for a certain determinant construct score). Each ceiling line's slope and intercept facilitate quantifying the strength of the necessity condition via the necessity effect size *d*; bottleneck tables offer further insights into the nature of the necessity conditions. Two articles in this special issue also make use of the NCA, thereby showcasing the potentials of this multimethod approach. Damberg et al. (2023) complement their standard PLS-SEM analysis with an NCA, showing that the relationships between corporate reputation, its determinants, and consumers' (sustainable) satisfaction are indeed necessary. Tiwari et al. (2023) run an NCA on their technology acceptance model to further the understanding of factors that drive travel app use. For example, their analysis shows that the technology's relative advantage and compatibility act as necessary conditions for perceived usefulness but not perceived enjoyment.

While the NCA offers an alternative perspective on the nature of model relationships, researchers have also proposed means to substantiate the hypothesized model structure. Inspired by machine learning, researchers have used the construct scores produced by the PLS-SEM algorithm as input for artificial neural networks (ANN). ANN simulate information processing through different layers of neurons in the brain's nervous system. This processing is characterized by activation functions, which dictate how an input translates into an output via hidden layers of neurons (also referred to as forward propagation). Using training data where the input and outputs are known, researchers then estimate the weights that characterize the relationships between the nodes. Prediction errors are then used to adjust the weights ex post (also referred to as backward propagation); nodes with higher errors are given lower weights, while nodes with smaller errors are weighted more strongly in the network. Forward and backward propagation alternate until the model's prediction error reaches a predetermined limit or a set number of iterations is being reached (e.g., Hair et al. 2020). The logic behind ANN can readily be transferred to PLS path models where constructs can be conceived as neurons linked via inner model weights (i.e., path relationships). While ANN allow for the specification of multiple layers, all the neurons from one layer are related to the neurons from the immediate previous and following layers. This design feature of ANN is likely to produce a mismatch between the network and the PLS path model, where no such requirement exists. Hence, when using the construct scores from a previous PLS-SEM analysis as input for the ANN estimation, researchers typically estimate the network layer-by-layer. When jointly applying PLS-SEM and ANN, researchers also need to be aware that PLS-SEM seeks to maximize in-sample prediction, while ANN analyses focus on maximizing out-of-sample prediction. As such, ANN-based robustness checks offer a valuable addition to predictive power analyses on the grounds of techniques such as $\text{PLS}_{\text{predict}}$ (Shmueli et al. 2016, 2019) or the cross-validated predictive ability test (Liengaard et al. 2019; Sharma et al. 2023), while considering nonlinearities in the model relations. Overall, ANN and PLS-SEM may be viewed as synergistic in that the PLS path model offers a logical framework for the neural network, while the neural network can furnish efficient parameter estimates for the structural model relations. Mkedder et al.'s (2023) paper published in this special issue considers this approach in order to evaluate the PLS path model's robustness in the context of virtual goods purchases.

Another area of methodological development relates to the specification, estimation, and validation of more complex model relationships such as mediating effects. Mediating effects assume that an antecedent construct impacts a target construct through a sequence of one or more intervening constructs, referred to as mediators. By analyzing sequences of relationships, researchers shed light on the mechanisms that underlie the assumed cause-effect relationships (Nitzl et al. 2016). When estimating such effects, researchers have typically considered relatively simple mediation models with one or very few mediators whose effects they considered in isolation. With the increasing dissemination of the PLS-SEM method, mediation analyses have also become more complex. A prominent example is the analysis of conditional mediation models where mediators and moderators interact. For example, the indirect effect between an antecedent and a target construct may depend on a moderator, implying that the mediating effect is conditional upon the values of the moderator (Cheah et al. 2021). PLS-SEM proves particularly useful for analyzing such effects. Unlike PROCESS-based analyses that use the construct scores from a previous analysis as input (Hayes 2018), PLS-SEM estimates reflect the entire model structure across different layers of constructs while accounting for measurement error (Hair et al. 2022). Researchers analyzing mediating effects between latent variables should therefore rely on PLS-SEM (Sarstedt et al. 2020). Chang et al.'s (2023) paper published in this special issue considers such a complex mediation model type. Their analysis shows that the mediating role of engagement in the relationship between consumers' technology experience and their intention to use a new technology depends on privacy concerns. Sarstedt and Moisescu (2023) note that the analysis of such mediating effects can come with a substantial level of uncertainty, especially when more than one configuration of a mediating effect is plausible. To identify the "best" mediation model in such a setting, researchers rely on information-theoretic model selection criteria (Burnham and Anderson 2002), whose values may, however, give false confidence in the results' adequacy. Addressing this concern, Sarstedt and Moisescu's (2023) paper published in this special issue introduces a procedure to quantify the metrological uncertainty (Rigdon et al. 2020; Rigdon and Sarstedt 2022) inherent in the comparison of different mediation models. Specifically, their procedure uses information-theoretic model selection criteria to weigh model-specific bootstrap samples in order to adjust the model parameters' confidence intervals (Rigdon et al. 2023).

The special issue concludes with two additional review articles, whose topics are likely to be relevant for many researchers working with PLS-SEM. Cheah et al. (2023) present a review of version 4 of SmartPLS (Ringle et al. 2022), which—according to recent reviews (Sarstedt et al. 2022; Wang et al. 2023; Zeng et al. 2021)—is the most frequently used software program for conducting PLS-SEM analyses. The authors review the program's core features vis-à- vis version 3 (Ringle et al. 2015)—see Sarstedt and Cheah (2019) for an earlier review. Finally, Gironda (2023) presents a review of the second edition of Hair et al.'s (2024) book *Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM)*, which covers several of the extensions used in this special issue's papers.

We believe that the research papers of this issue not only showcase the potentials of using advanced modeling and assessment routines in PLS-SEM, but also offer various avenues for further research in this rapidly emerging field. For example, some researchers equate formative measurement with composite models—as assumed by PLS-SEM—and reflective measurement with factor models—as assumed by covariance structure analysis (Cho et al. 2022) which, however, confuses the measurement theory layer with the model layer (e.g., Sarstedt et al. 2016). Addressing this concern, more research is needed to conceptually distinguish composite models and factor models. We also believe that further development of the necessity logic in the context of PLS-SEM hold considerable promise, for example, by adopting the multiple NCA (Dul 2023). Finally, recent advances in model assessment such as Liengaard et al.'s (2021) CVPAT may be extended to offer a broader range of predictive benchmarks for PLS path models.

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References

Basco, R., J.F. Hair, C.M. Ringle, and M. Sarstedt. 2022. Advancing family business research through modeling nonlinear relationships: Comparing PLS-SEM and multiple regression. *Journal of Family Business Strategy* 12 (3): 100457.

Becker, J.-M., D. Proksch, and C.M. Ringle. 2022. Revisiting Gaussian copulas to handle endogenous regressors. *Journal of the Academy of Marketing Science* 50 (1): 46–66.

Burnham, K.P., and D.R. Anderson. 2002. *Model Selection and Multimodel Inference*, 2nd ed. New York, NY: Springer.

Chang, Y.-S., R. Konar, J.H. Cheah, and X.-J. Lim. 2023. Does privacy still matter in smart technology experience? A conditional mediation analysis. *Journal of Marketing Analytics*. https://doi.org/10.1057/s41270-023-00240-8.

Cheah, J.H., F. Magno, and F. Cassia. 2023. Reviewing the SmartPLS 4 software: The latest features and enhancements. *Journal of Marketing Analytics*. https://doi.org/10.1057/s41270-023-00266-y.

Cheah, J.H., C. Nitzl, J.L. Roldán, G. Cepeda-Carrión, and S.P. Gudergan. 2021. A primer on the conditional mediation analysis in PLS-SEM. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems* 52: 43–100.

Cho, G., M. Sarstedt, and H. Hwang. 2022. A comparison of covariance structure analysis, partial least squares path modeling and generalized structured component analysis in factor- and composite models. *British Journal of Mathematical and Statistical Psychology* 75 (2): 220–251.

Crespo, C.F., A.G. Ferreira, and R.M. Cardoso. 2023. The influence of storytelling on the consumer–brand relationship experience. *Journal of Marketing Analytics* 11 (1): 41–56.

Damberg, S., Y. Lium, and C.M. Ringle. 2023. Does culture matter? Corporate reputation and sustainable satisfaction in the Chinese and German banking sector. *Journal of Marketing Analytics*. https://doi.org/10.1057/s41270-023-00259-x.

Damberg, S., M. Schwaiger, and C.M. Ringle. 2022. What's important for relationship management? The mediating roles of relational trust and satisfaction for loyalty of cooperative banks' customers. *Journal of Marketing Analytics* 10 (1): 3–18.

Dul, J. 2016a. Identifying single necessary conditions with NCA and fsQCA. *Journal of Business Research* 69 (4): 1516–1523.

Dul, J. 2016b. Necessary condition analysis (NCA): Logic and methodology of "necessary but not sufficient" causality. *Organizational Research Methods* 19 (1): 10–52.

Dul, J. 2023. Necessary condition analysis (NCA) with R (Version 3.3.3): A quick start guide. Available at SSRN: https://ssrn.com/abstract=2624981

Dul, J., S. Hauff, and R.B. Bouncken. 2023. Necessary condition analysis (NCA): Review of research topics and guidelines for good practice. *Review of Managerial Science* 17 (2): 683–714.

Gironda, J. 2023. Review of advanced issues in partial least squares structural equation modeling, Second Edition, *Journal of Marketing Analytics*, Advance online publication.

Guenther, P., M. Guenther, C.M. Ringle, G. Zaefarian, and S. Cartwright. 2023. Improving PLS-SEM use for business marketing research. *Industrial Marketing Management* 111: 127–142.

Hair, J.F., and D.E. Harrison. 2021. *Essentials of Marketing Analytics*. New York, NY: McGraw-Hill.

Hair, J.F., C.L. Hollingsworth, A.B. Randolph, and A.Y.L. Chong. 2017. An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems* 117 (3): 442–458.

Hair, J.F., G.T.M. Hult, C.M. Ringle, and M. Sarstedt. 2022. *A primer on partial least squares structural equation modeling (PLS-SEM)*, 3rd ed. Thousand Oaks, CA: Sage.

Hair, J.F., M. Sarstedt, C.M. Ringle, and S.P. Gudergan. 2024. *Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 2nd ed. Thousand Oaks, CA: Sage.

Hayes, A.F. 2018. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-based Approach*. New York, NY: The Guilford Press.

Leong, K.Y., J.S.Y. Ho, S. Tehseen, E. Yafi, and T.-H. Cham. 2023. The intangible values of live streaming and their effect on audience engagement. *Journal of Marketing Analytics*. https://doi.org/10.1057/s41270-023-00247-1.

Liengaard, B., P.N. Sharma, G.T.M. Hult, M.B. Jensen, M. Sarstedt, J.F. Hair, and C.M. Ringle. 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*. Heidelberg: Physica.

Mkedder, N., and F.Z. Özata. 2023. I will buy virtual goods if I like them: A hybrid PLS-SEM-artificial neural network (ANN) analytical approach. *Journal of Marketing Analytics*. https://doi.org/10.1057/s41270-023-00252-4.

Nitzl, C., J.L. Roldan, and G. Cepeda. 2016. Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems* 116 (9): 1849–1864.

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., Y. Hadavi, and 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: 10–23.

Richter, N.F., S. Hauff, C.M. Ringle, and S.P. Gudergan. 2022. The use of partial least squares structural equation modeling and complementary methods in international management research. *Management International Review* 62 (4): 449–470.

Richter, N.F., S. Hauff, C.M. Ringle, M. Sarstedt, A. Kolev, and S. Schubring. 2023. How to apply necessary condition analysis in PLS-SEM. In H. Latan, J. F. Hair, and R. Noonan (Eds.), Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues, and Applications (2nd ed.). Cham: Springer.

Richter, N.F., S. Schubring, S. Hauff, C.M. Ringle, and M. Sarstedt. 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.

Rigdon, E.E., and M. Sarstedt, M. 2022. Accounting for uncertainty in the measurement of unobservable marketing phenomena. In: H. Baumgartner and B. Weijters (Eds.), Review of Marketing Research, Vol. 19 (pp. 53–73). Bingley, UK: Emerald.

Rigdon, E.E., M. Sarstedt, and J.-M. Becker. 2020. Quantify uncertainty in behavioral research. *Nature Human Behaviour* 4: 329–331.

Rigdon, E.E., M. Sarstedt, and O.I. Moisescu. 2023. Quantifying model selection uncertainty via bootstrapping and Akaike weights. *International Journal of Consumer Studies* 47 (4): 1596–1608.

Ringle, C.M., M. Sarstedt, N. Sinkovics, and R.R. Sinkovics. 2023. A perspective on using partial least squares structural equation modelling in data articles. *Data in Brief* 48: 109074.

Ringle, C.M., S. Wende, and J.-M. Becker .2015. SmartPLS 3 [Computer software]. Retrieved from http://www.smartpls.com

Ringle, C.M., S. Wende, and J.-M. Becker. 2022. SmartPLS 4 [Computer software]. Retrieved from http://www.smartpls.com

Russo, D., and K.-J. Stol. 2021. PLS-SEM for software engineering research: An introduction and survey. *ACM Computing Surveys* 54 (4): 1–38.

Sarstedt, M., and J.-H. Cheah. 2019. Partial least squares structural equation modeling using SmartPLS: A software review. *Journal of Marketing Analytics* 7 (3): 196–202.

Sarstedt, M., J.F. Hair, J.-H. Cheah, J.-M. Becker, and C.M. Ringle. 2019. How to specify, estimate, and validate higher-order models. *Australasian Marketing Journal* 27 (3): 197–211.

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

Sarstedt, M., J.F. Hair, M. Pick, B.D. Liengaard, L. Radomir, and C.M. Ringle. 2022. Progress in partial least squares structural equation modeling use in marketing research in the last decade. *Psychology & Marketing* 39 (5): 1035–1064.

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

Sarstedt, M., and O.I. Moisescu. 2023. Quantifying uncertainty in PLS-SEM-based mediation analyses. *Journal of Marketing Analytics*. https://doi.org/10.1057/s41270-023-00231-9.

Sharma, P.N., B.D. Liengaard, J.F. Hair, M. Sarstedt, and C.M. Ringle. 2023. 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.

Shmueli, G., S. Ray, J.M. Velasquez Estrada, and S.B. Chatla. 2016. The elephant in the room: Evaluating the predictive performance of PLS models. *Journal of Business Research* 69 (10): 4552–4564.

Shmueli, G., M. Sarstedt, J.F. Hair, J.-H. Cheah, H. Ting, and C.M. Ringle. 2019. Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing* 53 (11): 2322–2347.

Soares, J.C., R. Limongi, J.H. De Sousa Júnior, W. Soares Santos, M. Raasch, and L. Hoeckesfeld. 2023. Assessing the effects of COVID-19-related risk on online shopping behavior. *Journal of Marketing Analytics* 11 (1): 82–94.

Sternad Zabukovšek, S., S. Bobek, U. Zabukovšek, Z. Kalinić, and P. Tominc. 2022. Enhancing PLS-SEM-enabled research with ANN and IPMA: Research study of enterprise resource planning (ERP) systems' acceptance based on the technology acceptance model (TAM). *Mathematics* 10 (9): 1379.

Tiwari, P., R.P.S. Kaurav, and K.Y. Koay. 2023. Understanding travel apps usage intention: Findings from PLS and NCA. *Journal of Marketing Analytics*. https://doi.org/10.1057/s41270-023-00258-y.

Wang, S., J.-H. Cheah, C.Y. Wong, and T. Ramayah. 2023. Progress in partial least squares structural equation modeling use in logistics and supply chain management in the last decade: A structured literature review. *International Journal of Physical Distribution & Logistics Management*. https://doi.org/10.1108/IJPDLM-06-2023-0200.

Wold, H. 1982. Soft modeling: The basic design and some extensions. In K.G. Jöreskog and H. Wold (Eds.), Systems Under Indirect Observations. Part II (pp. 1–54). Amsterdam: North-Holland.

Zeng, N., Y. Liu, P. Gong, M. Hertogh, and M. König. 2021. Do right PLS and do PLS right: A critical review of the application of PLS-SEM in construction management research. *Frontiers of Engineering Management* 8: 356–369.

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