ACM-SIGMIS DATA BASE for Advances in Information Systems

Call for papers

Using advanced PLS-SEM methods to further the understanding of MIS phenomena

Guest editors

Pratyush N. Sharma, University of Delaware
pnsharma@udel.edu

Marko Sarstedt, Otto-von-Guericke University Magdeburg and Monash University Malaysia
marko.sarstedt@ovgu.de

Christian M. Ringle, Hamburg University of Technology and University of Waikato
c.ringle@tuhh.de

Scope of the special issue

Partial least squares structural equation modeling (PLS-SEM) has gained considerable attention in management information systems (MIS) research (Hair et al. 2017; Ringle et al. 2012; Petter 2018). Many theoretical models highly relevant to MIS (e.g., TAM, UTAUT, and derivatives) and the broader management field (e.g., the American customer satisfaction index) have relied heavily on PLS-SEM in their development. As a composite-based approach to SEM, PLS-SEM aims at maximizing the explained variance in dependent constructs in the path model (e.g., technology adoption and use) and allows researchers to simultaneously estimate interrelationships involving a variety of constructs and indicators (Petter 2018). As such PLS-SEM is perfectly suited for today's data-driven economy, where MIS researchers seek to support decision makers by extending or generating theories and assessing their practical utility to assist policy decisions.

A main objective of MIS research is to create theories that offer both explanation and prediction of the phenomena of interest (Gregor 2006; Grover et al. 2008). While theoretical development in MIS research has been predominantly driven by an explanation-oriented focus (e.g., model fit, R^2), few or no benchmarks of the actual (out-of-sample) predictive performance of MIS models currently exist (Shmueli and Koppius 2011). Ignoring the out-of-sample properties means that there is a lack of evidence regarding whether the models will fit other datasets well (Petter 2018). Prediction-oriented assessments can aid theory generation and enhancement via comparison, relevance assessment, improvement in measures, and benchmarking the predictability of MIS phenomena (Hofman, Sharma and Watts 2017).

Furthermore, the profusion of model alternatives and the lack of model comparisons have resulted in fragmented theoretical development (Gray & Cooper 2010; Sharma et al. 2019). For example, Grover (2013, p. 277) questions monistic theorization in MIS research, where "the same phenomenon (e.g., IT outsourcing) might be examined using five different theoretical perspectives in five different papers by five different teams. This blocks vibrancy of discourse, consolidation of knowledge, and innovation." In light of these issues, MIS theorists have long called for model comparisons to create holistic theory, such as Roberts and Grover (2009, p. 89) who, in their review of SEM techniques in

MIS research, note that, "…specifying alternative models, is useful in theory building because it gives the researcher alternative perspectives concerning the focal phenomena."

The latest methodological developments in PLS-SEM seek to address this empirical imbalance in MIS research. New avenues have been opened for improvements in existing - and the creation of new - measures and theories, in particular, via out-of-sample predictive assessments and comparisons (Shmueli et al. 2016; Sharma et al. 2018, Sharma et al. 2019). Model assessments and comparisons using the prediction-oriented lens can help cohesive theoretical development by exploring the tension among theories (Grover 2013), benchmarking their predictive strengths relative to each other, and providing better understanding of the limits of how well the models fit real-world data (Gray and Cooper, 2010; Shmueli and Koppius 2011).

Similarly, novel PLS-SEM-based complementary methods allow researchers to assess the robustness of their models (Sarstedt et al. 2019). Such robustness checks are fundamental for theory testing and development and have become common in regression-based studies, where researchers examine "how certain 'core' regression coefficient estimates behave when the regression specification is modified in some way, typically by adding or removing regressors." (Lu and White 2014, p. 194). Examples include methods that allow assessment of nonlinear effects (Sarstedt et al. 2019), endogeneity (Hult et al. 2018), and unobserved heterogeneity (Schlittgen et al. 2016).

This special issue focuses on the application of advanced techniques now available in PLS-SEM to stimulate innovative and fresh investigation of core MIS phenomena, and promote novel theoretical development. Topics include, but are not limited to:

1. Extending or consolidating MIS models and theories by connecting them with insights from related disciplines,
2. Model comparisons to further the understanding of core aspects of MIS research, and generate novel theory,
3. Exploring the interplay between explanation and prediction in MIS model assessments,
4. Reconsidering the performance of prominent MIS models from a balanced explanation and prediction perspective,
5. Robustness checks of prominent MIS models, e.g., presence of nonlinear effects, endogenous factors, prediction-oriented segmentation analysis to identify and treat unobserved heterogeneity, measurement invariance of composite models, boundary testing,
6. Applications of latent class procedures to understand group-related differences in MIS-related perceptions and behaviors.

Submissions

The special issue is tied to the 2020 International Conference on Partial Least Squares Structural Equation Modeling (www.pls2020.org) to be held October 28-30, 2020 in Beijing, China. Outstanding papers presented at this conference will be invited for submission. These papers will then go through the regular journal review process. The guest editors will allow for a maximum of two revisions after which a final editorial decision will be made. The special issue is scheduled to appear in the second half of 2021. The submission deadline is **November 30, 2020**.

References

Franke, G. & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. Internet Research, in press.

Gray, P. H., & Cooper, W. H. (2010). Pursuing failure. Organizational Research Methods, 13(4), 620-643.

Gregor, S. (2006). The nature of theory in information systems. MIS Quarterly, 30(3), 611-642.

Grover, V. (2013). Muddling along to moving beyond in IS research: getting from good to great. Journal of the Association for Information Systems, 14(5), 274-282.

Grover, V., Lyytinen, K., Srinivasan, A., & Tan, B. C. (2008). Contributing to rigorous and forward thinking explanatory theory. Journal of the Association for Information Systems, 9(2), 40-47.

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

Henseler, J., Ringle, C.M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. International Marketing Review, 33(3), 405-431.

Hofman, J. M., Sharma, A., & Watts, D. J. (2017). Prediction and explanation in social systems. Science, 355 (6324), 486-488.

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.

Lu, X. & White, H. (2014). Robustness checks and robustness tests in applied economics. Journal of Econometrics, 178, 194–206.

Petter, Stacie (2018). Haters gonna hate: PLS and information systems research. ACM SIGMIS Database: The DATABASE for Advances in Information Systems, 49(1), 10-13.

Ringle, C.M., Sarstedt, M., & Straub, D.W. (2012). Editor's comments: a critical look at the use of PLS-SEM in MIS quarterly. MIS Quarterly, 36(1), pp. iii-xiv.

Roberts, N., & Grover, V. (2009). Theory development in information systems research using structural equation modeling: evaluation and recommendations. In: Y. K. Dwivedi, B. Lal, M. D. Williams, S. L. Schneberger, & M. Wade (Eds.), Handbook of research on contemporary theoretical models in information systems (pp. 77-94). Hershey: IGI Global.

Sarstedt, M., Ringle, C.M., Cheah, J.-H., Ting, H., Moisescu, O. I., & Radomir, L. (2019). Structural model robustness checks in PLS-SEM. Tourism Economics, in press.

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.

Sharma, P.N., Sarstedt, M., Shmueli, G., Kim, K.H. (†), & Thiele, K.O. (2019). PLS-based model selection: The role of alternative explanations in information systems research. Journal of the Association for Information Systems, in press.

Sharma, P.N., Shmueli, G., Sarstedt, M., Danks, N., & Ray, S. (2018). Prediction-oriented model selection in partial least squares path modeling. Decision Sciences, in press.

Shmueli, G. & Koppius, O. R. (2011). Predictive analytics in information systems research. MIS Quarterly, 35(3), 553-572.

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