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EDITORIAL

Advances in composite-based structural equation modeling

Marko Sarstedt[1,2] · Heungsun Hwang[3]

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Structural equation modeling (SEM) has become a quasi-standard tool for analyzing complex inter-relationships between observed and latent variables. Two conceptually different approaches to SEM have been proposed: factor- vs. component-based SEM. Factor-based SEM approximates latent variables by common factors as in common factor analysis, whereas component-based SEM regards them as weighted composites of observed variables as in multivariate statistics such as canonical correlation analysis and principal component analysis. Factor-based SEM is represented by covariance structure analysis, whereas composite-based SEM includes generalized structured component analysis (GSCA; Hwang and Takane 2004), partial least squares (PLS; Lohmöller 1989), regularized generalized canonical correlation analysis (Tenenhaus and Tenenhaus 2011), and several others. Although factor-based SEM remains prevalent in practice, numerous methodological advances (e.g., Hwang et al. 2010; Suk and Hwang 2016; Schlittgen et al. 2016) and tutorial articles, which have made the methods accessible to applied researchers (e.g., Hair et al. 2019, 2020; Sarstedt et al. 2019), have contributed to component-based SEM's growing popularity in recent years.

Parallel to these developments, recent research in psychometrics calls the central tenets of the common factor model into question. For example, Rigdon (2016, p. 602) notes that "common factor proxies cannot be assumed to carry greater significance than composite proxies in regard to the existence or nature of conceptual variables." Similarly, Rhemtulla et al. (2020) observe that "there is a growing appreciation within some areas of psychology that the latent variable model may not be the right model to capture relations between many psychological constructs and their observed indicators." This notion has been echoed in numerous

✉ Marko Sarstedt
marko.sarstedt@ovgu.de

Heungsun Hwang
heungsun.hwang@mcgill.ca

1 Otto-Von-Guericke-University Magdeburg, Magdeburg, Germany

2 Monash University Malaysia, Subang Jaya, Malaysia

3 McGill University, Montreal, Canada

other publications in a variety of fields (e.g., Hair and Sarstedt 2019; Henseler et al. 2014; Rigdon 2012; Rigdon et al. 2017). More fundamentally, Rigdon et al. (2019) show that the indeterminacy of common factors creates a band of (metrological) uncertainty in the relationship between the factor inside the model and any variable outside the model—including the conceptual variable that the factor seeks to represent (Steiger 1979). The standard treatment of construct measures in covariance structure analysis—such as using only few indicators to measure a construct—increases factor indeterminacy and hence the degree of metrological uncertainty, hindering the replicability of behavioral science research (Rigdon et al. 2020). These results do not imply that component-based SEM techniques excel covariance structure analysis per se. However, they cast doubt on the universal applicability of the common factor model.

While there has always been a controversy between factor-based and composite-based approaches to SEM, recently, the tenor of this controversy has become more intense. Whereas some researchers strongly advocate the use of component-based SEM (Sarstedt et al. 2016), others believe that this approach should be abandoned (Rönkkö et al. 2016). The debates also led to a diversification of the composite-based SEM community, with differing viewpoints on the nature of measurement, the role of model fit, and the methods' scope of application. For example, Hwang et al. (2017) proposed GSCA with measurement errors incorporated, called GSCA_M, which aims to estimate the parameters of factor-based SEM via GSCA. Similarly, whereas some researchers stress the need to consider model fit metrics, others emphasize statistics for assessing a model's out-of-sample predictive accuracy (Cho et al. 2019; Hair et al. 2019; Shmueli et al. 2019).

In light of these controversies and debates, composite-based SEM is at the crossroads. The following years will show under which conditions composite-based-SEM methods will routinely be used and how sustainable their current popularity will be. With these developments in mind, this special issue of *Behaviormetrika* seeks to serve as a platform for advancing and furthering our understanding of composite-based SEM methods.

The lead article in this special issue by Hwang et al. (2020) contrasts PLS–SEM and GSCA, arguably the most prominent composite-based SEM methods in the field. After the conceptual comparison of the two approaches, the authors present the result of a concept analysis of methodological research on PLS–SEM and GSCA to identify dominant topics that characterize the joint research domain. The results illustrate the field's maturation, showing, for example, that researchers have become aware of the conceptual differences between composite and factor models and their implications for the methods' performance. Based on the results, the authors identify numerous research avenues for research on composite-based SEM methods.

Tying in with this lead article, Cho and Choi (2020) offer a comparison of PLS–SEM and GSCA on the grounds of a simulation study. For this purpose, the authors propose a new data generation approach where components are constructed to explain the variances of their indicators as well as those of endogenous components. Their simulation study considers different measurement model set-ups and PLS–SEM-based estimation modes. Their result pattern is similar to Hair et al.'s (2017), in that GSCA recovers measurement model parameters more effectively than

PLS–SEM, while both approaches perform very similarly with regard to structural model parameter recovery.

The third paper in this special issue illustrates the use of GSCA in the specific context of brain connectivity research. Using data collected during encoding of source memory in a functional magnetic resonance imaging (fMRI) study, Jung et al. (2020) demonstrate how to specify and evaluate a fully and bidirectionally connected structural model of brain connectivity using GSCA. This application to fMRI data nicely ties in with the increasing number of studies that use composite-based SEM in fields other than the social sciences to explore natural/biological phenomena (Sarstedt 2019). Based on their results, the authors discuss various implications for future extensions of the GSCA approach.

The fourth paper by Ryoo et al. (2020) offers such an extension by combining GSCA with optimal scaling and fuzzy clustering to capture unobserved class-level heterogeneity in the data. The authors test their new approach on real-world data to show that it yields the same results as maximum likelihood-based latent class analysis, while avoiding identification issues. The new approach, therefore, nicely expands the applicability and capability of latent class analysis in composite-based SEM.

The final paper in this special issue by Schamberger et al. (2020) offers a robust variant of standard PLS–SEM and consistent PLS–SEM (PLSc-SEM). Their simulation study with various population models and simulation conditions underlines the efficacy of the approach to reliably recover model estimates in the presence of outliers.

We are confident that the papers in this special issue will trigger significant interest in the field and inspire exciting follow-up research. We would like to thank Behaviormetrika's Editor-in-Chief, Maomi Ueno, for giving us the opportunity to edit this special issue. In addition, we would like to thank the numerous reviewers without whom this special issue would not have been possible—thank you!

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