Structural Equation Modeling with Factors and Composites: A Comparison of Four Methods

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ABSTRACT

Recent methodological developments building on partial least squares (PLS) techniques and related ideas have significantly contributed to bridging the gap between factor-based and composite-based structural equation modeling (SEM) methods. PLS-SEM is extensively used in the field of e-collaboration, as well as in many other fields where multivariate statistical analyses are employed. The author compares results obtained with four methods: covariance-based SEM with full information maximum likelihood (FIML), factor-based SEM with common factor model assumptions (FSEM1), factor-based SEM building on the PLS Regression algorithm (FSEM2), and PLS-SEM employing the Mode A algorithm (PLSA). The comparison suggests that FSEM1 yields path coefficients and loadings that are very similar to FIML’s; and that FSEM2 yields path coefficients that are very similar to FIML’s and loadings that are very similar to PLSA’s.

KEYWORDS

Endogeneity, Measurement Error, Monte Carlo Simulation, Partial Least Squares, Path Bias, Structural Equation Modeling, Variation Sharing

INTRODUCTION

Structural equation modeling (SEM) methods and software tools allow researchers to simultaneously define and test measurement and structural models involving latent variables. Mathematically such variables are, at the population level, weighted aggregations of indicators (quantitative responses in questionnaires) and measurement errors. In this context, structural models (a.k.a. inner models) are often assessed through path coefficients among latent variables, and measurement models (a.k.a. outer models) are often assessed through loadings among indicators and their respective latent variables.

The relatively recent popularity of partial least squares (PLS) techniques and their use in SEM has led to strong criticism from some quarters. This criticism is primarily due to the fact that classic PLS-SEM methods are composite-based, not factor-based. That is, in classic PLS-SEM methods latent variables are estimated as weighted aggregations of indicators, without the inclusion of measurement errors. The latter, the measurement errors, can be seen as “extra” indicators that complement the actual indicators; together, actual indicators and measurement errors make up factors. Without measurement
errors, the use of composites instead of factors leads to some known sources of bias. Notably, path coefficients tend to be attenuated with respect to their corresponding true values.

Recent methodological developments building on PLS techniques and related ideas have significantly contributed to bridging the gap between factor-based and composite-based SEM methods. At the time of this writing at least one widely used PLS-SEM software tool, namely WarpPLS (Kock, 2015a), implemented these developments. Factor-based SEM builds on classic PLS-SEM techniques as well as on more advanced and modern techniques. In it, both factors and composites are estimated, with the factors being derived from the composites. For an overview and discussion of classic PLS-SEM techniques, see Kock & Mayfield (2015). For a broad discussion of the two-stage process whereby factors and composites are estimated in factor-based SEM, see Kock (2015b).

Partly due to the ease-of-use and extensive features of software tools such as WarpPLS, which we use here in our illustrative analyses because it provides the most extensive set of features among comparable software, PLS-SEM is now extensively used in the field of e-collaboration (Kock, 2005; 2008; 2010; 2013; 2014), as well as in many other fields where multivariate statistical analyses are employed (see, e.g., Kock & Gaskins, 2014; Kock & Verville, 2012).

In this study, we compare results obtained with four SEM methods: covariance-based SEM with full information maximum likelihood (FIML), factor-based SEM with common factor model assumptions (FSEM1), factor-based SEM building on the PLS Regression algorithm (FSEM2), and PLS-SEM employing the Mode A algorithm (PLSA). The comparison suggests that FSEM1 yields path coefficients and loadings that are very similar to FIML’s; and that FSEM2 yields path coefficients that are very similar to FIML’s and loadings that are very similar to PLSA’s.

**ILLUSTRATIVE MODEL AND DATA**

Our discussion is based on the illustrative model depicted in Figure 1, which builds on actual empirical studies in the field of e-collaboration (Kock, 2005; 2008; Kock & Lynn, 2012). This illustrative model addresses the organizational effect of the use of an internal e-collaboration management tool with social networking capabilities (EM) on job performance (JP), an effect that is mediated by intermediate effects on job satisfaction (JS) and job innovativeness (JI).

The figure has been created with the SEM analysis software WarpPLS (Kock, 2015a). Therefore, it employs the software’s standard notation for summarized latent variable description. In it the

**Figure 1. Illustrative model used**

![Illustrative model](image)

*Notes: EM = internal e-collaboration management tool with social networking capabilities; JS = job satisfaction; JI = job innovativeness; JP = job performance; notation under latent variable acronym describes measurement approach and number of indicators, e.g., (R)i = reflective measurement with 9 indicators.*
The Support of Virtual 3D Worlds for Enhancing Collaboration in Learning Settings
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