Structural equation modeling with factors and composites: A comparison of four methods

Ned Kock

Full reference:

Kock, N. (2017). Structural equation modeling with factors and composites: A comparison of four methods. *International Journal of e-Collaboration*, 13(1), 1-9.

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. We compare 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: Partial Least Squares; Structural Equation Modeling; Measurement Error; Path Bias; Variation Sharing; Monte Carlo Simulation; Endogeneity.

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).

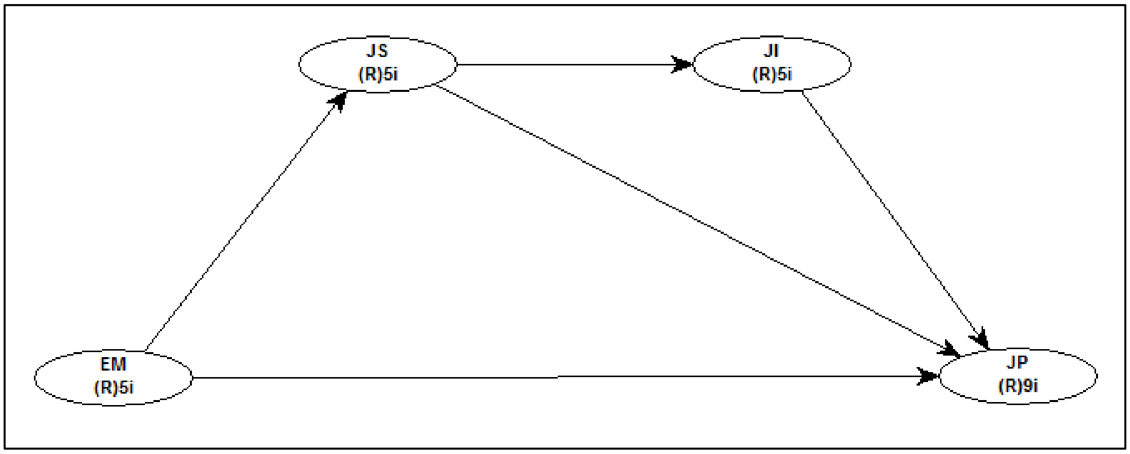
Partly due to the ease-of-use and extensive features of software tools such as WarpPLS, which we use here in our illustrative analyses because it provides the most extensive set of features among comparable software, PLS- SEM is now extensively used in the field of e-collaboration (Kock, 2005; 2008; 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).

Figure 1: Illustrative model used



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)9i = reflective measurement with 9 indicators.

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 alphanumeric combination under each latent variable's label (e.g., "JP") in the model describes the measurement approach used for that latent variable and the number of indicators. For example "(R)9i" means reflective measurement with 9 indicators.

We employed the Monte Carlo method (Kock, 2016; Robert & Casella, 2005) to create sample data based on this model, as well as assumptions grounded on past empirical research. The sample we created had 1000 cases; or rows in the data table. The number of columns was 24, which was the total number of indicators used. We assumed that the indirect relationship between EM and JP was fully mediated by the network of links involving the latent variables JS and JI.

The above can be restated as follows. We assumed a neutral direct effect EM→JP at the population level. Nevertheless, the EM→JP link must be included in SEM analyses aimed at testing the model. The reason for this is that the indirect relationship between EM and JP at the population level, mediated by the network of links involving JS and JI, induces endogeneity. More specifically, the error term for JP is correlated with EM. Adding the EM→JP link in SEM analyses provides a partial correction for the bias stemming from this situation.

The SEM methods compared

This methodological study compared 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). A brief description of these methods is provided below.

Covariance-based SEM with full information maximum likelihood (FIML). This is the classic method for covariance-based SEM, where convergence to a solution occurs via minimization of the overall difference between the model-implied and empirical indicator covariance matrices. This method explicitly accounts for measurement error, but does not generate estimates of either composites or factors. Prior to the development of tools such as WarpPLS, this has generally been the most widely used method for SEM (Kock & Lynn, 2012).

Factor-based SEM with common factor model assumptions (FSEM1). This method generates estimates of both true composites and factors, in two stages, explicitly accounting for measurement error (Kock, 2015b). Like the FIML method, this FSEM1 method is fully compatible with common factor model assumptions. In its first stage, this method employs a new "true composite" estimation sub-algorithm, which estimates composites based on mathematical equations that follow directly from the common factor model. The second stage employs a new "variation sharing" algorithm, which can be seen as a "soft" version of the classic expectation-maximization algorithm used in maximum likelihood estimation, with apparently faster convergence and nonparametric properties.

Factor-based SEM building on the PLS Regression algorithm (FSEM2). This method first estimates composites via PLS Regression (Kock & Mayfield, 2015), whereby the latent variables are estimated without taking the inner model into consideration. This FSEM2 method then proceeds by estimating factors employing the new variation sharing algorithm, which is also used in the FSEM1 method. Unlike FSEM1, this method does not enforce the common factor model assumption that indicator error terms are uncorrelated, which past research suggests to be a rare occurrence in actual empirical data. Among the factor-based methods implemented through WarpPLS, this factor-based SEM method can be seen as the closest to Wold's original PLS design (Kock, 2015a).

PLS-SEM employing the Mode A algorithm (PLSA). This is by far the most widely used PLS-SEM method in practice. The Mode A is often referred to as the "reflective" mode, which is arguably incorrect because both reflective and formative latent variables can be used with this algorithm (Kock & Mayfield, 2015). In this method the inner model influences the outer model through path coefficients and correlations, depending on whether the links go into or out from each latent variable, respectively.

We used R 3.2.2 and the package lavaan 0.5-19 (Rosseel, 2012) for the SEM analysis employing FIML. We used WarpPLS 5.0 (Kock, 2015a) for the SEM analyses employing FSEM1, FSEM2 and PLSA. The WarpPLS outer model analysis algorithm settings chosen were the following: "Factor-Based PLS Type CFM1" for FSEM1, "Factor-Based PLS Type REG1" for FSEM2, and "PLS Mode A" for PLSA.

Path coefficients and loadings

Table 1 shows the path coefficients estimated through each of the four methods. All methods yielded P values lower than 0.001, which are highly statistically significant, for the paths EM→JS, JS→JI, JS→JP and JI→JP. For the path EM→JP, the following P values were obtained from the SEM analyses: P=0.135 by FIML, P= 0.113 by FSEM1, P= 0.122 by FSEM2, and P=0.243 by PLSA. All of these P values for the path EM→JP suggest a statistically non-significant association between the variables EM and JP.

The small and non-significant path coefficients for EM→JP are a reflection of the population model. While there is no link between EM and JP at the population level, the network of links connecting these two variables leads to them being correlated. This same network of links leads to the endogeneity instance mentioned earlier: the error term for JP is correlated with EM. Therefore, when analyzing the samples we expected the path coefficients for EM→JP to be nonzero, and also non-significant, regardless of the method used. This is indeed what we observed.

As we can see, three methods yielded path coefficient estimates that were in general relatively close to one another: FIML, FSEM1 and FSEM2. These are factor-based methods, which take measurement error into account when generating estimates of path coefficients. We can also see that PLSA, a composite-based method, generally yielded path coefficient estimates that were uniformly lower than those generated by the other three factor-based methods.

Table 2 lists the loadings estimated through each of the four methods. Here we see a different pattern of similarities and differences than that of path coefficients. FIML and FSEM1 yielded loading estimates that were relatively close to one another. So did FSEM2 and PLSA. The loading estimates generated by these two latter methods (i.e., FSEM2 and PLSA) were generally higher than those estimated by FIML and FSEM1.

Table 1: Path coefficients

	FIML	FSEM1	FSEM2	PLSA
EM→JS	0.486	0.491	0.485	0.440
JS→JI	0.458	0.470	0.464	0.417
EM→JP	-0.035	-0.038	-0.037	-0.022
JS→JP	0.221	0.221	0.213	0.209
JI→JP	0.556	0.571	0.563	0.509

Table 2: Loadings

	FIML	FSEM1	FSEM2	PLSA
EM→EM1	0.898	0.893	0.904	0.905
EM→EM2	0.847	0.851	0.874	0.877
EM→EM3	0.803	0.810	0.850	0.846
EM→EM4	0.763	0.765	0.820	0.819
EM→EM5	0.700	0.696	0.774	0.776
JS→JS1	0.903	0.903	0.906	0.910
JS→JS2	0.844	0.833	0.872	0.875
JS→JS3	0.791	0.799	0.843	0.843
JS→JS4	0.769	0.772	0.824	0.824
JS→JS5	0.695	0.700	0.770	0.766
JI→JI1	0.896	0.898	0.903	0.905
JI→JI2	0.858	0.856	0.882	0.885
JI→JI3	0.804	0.811	0.846	0.845
JI→JI4	0.750	0.747	0.812	0.813
JI→JI5	0.683	0.677	0.761	0.759
JP→JP1	0.899	0.903	0.890	0.893
JP→JP2	0.855	0.856	0.862	0.864
JP→JP3	0.793	0.806	0.822	0.825
JP→JP4	0.767	0.780	0.798	0.799
JP→JP5	0.657	0.675	0.704	0.704
JP→JP6	0.628	0.650	0.681	0.686
JP→JP7	0.591	0.616	0.649	0.644
JP→JP8	0.528	0.546	0.590	0.586
JP→JP9	0.536	0.563	0.596	0.594

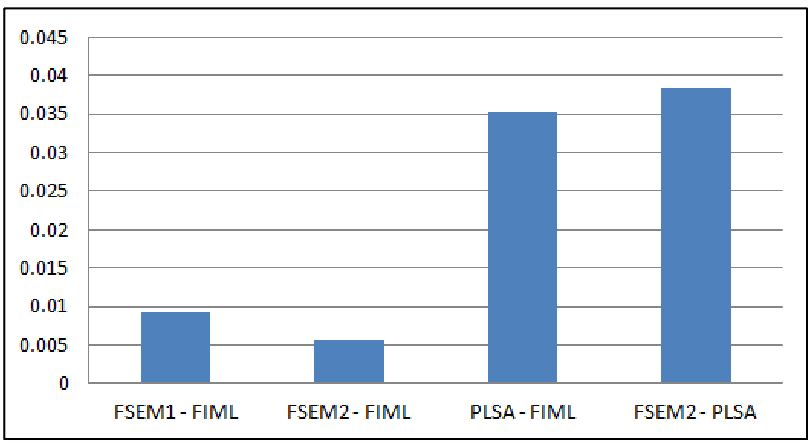
Many researchers, particularly those who are strong adherents to covariance-based SEM methods such as FIML, argue that a measurement model assessment building on a factor analysis cannot be properly conducted based on loadings generated through composite-based SEM methods such as PLSA. We can see here why this claim is often made. If loadings are higher, then measurement model assessment criteria based on loading thresholds (e.g., 0.5 or 0.7) are more easily achieved. And loadings were generally higher with FSEM2 and PLSA than with FIML and FSEM1.

However, the above argument has a fundamental flaw – it presupposes that the empirical data is sampled from a population that strictly conforms to the common factor model. Indeed, if the population from which the sample was drawn conforms strictly with common factor model assumptions, then the loadings generated by FIML and FSEM1 would provide the basis for a more conservative measurement model assessment than those generated by FSEM2 and PLSA. However, as noted earlier, common factor model assumptions do not normally hold with real (as opposed to simulated) empirical data.

Differences among path coefficients and loadings

Figure 2 shows illustrative differences among path coefficients estimated through the four methods. Four bars are shown; each representing the root-mean-square error (RMSE) calculated based on individual path coefficient differences. The RMSEs were calculated by averaging the squared differences among path coefficients, and taking the square root of this average. The RMSEs shown were chosen to illustrate differences and similarities between pairs of methods, with the matched methods selected based on the results presented earlier in table format.

Figure 2: Differences among path coefficients (RMSEs)

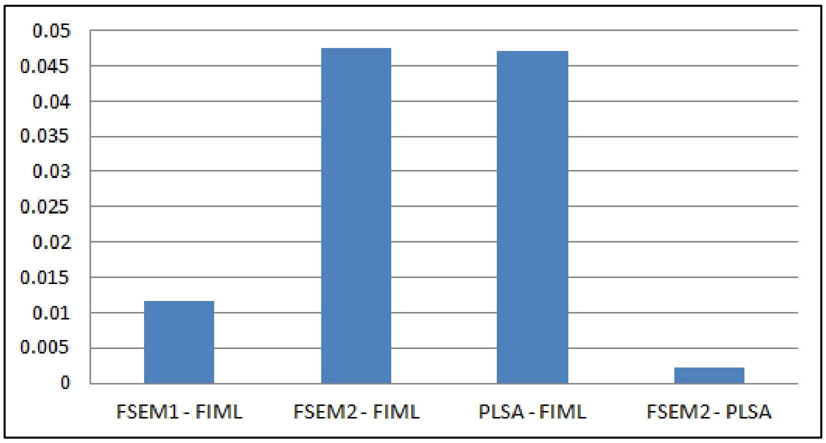


Each bar, being a RMSE contrasting two methods, can be seen as an aggregate measure reflecting the overall difference between the two methods in terms of path coefficients. For example, the first bar on the left shows the RMSE calculated based on the differences among path coefficients generated by the FSEM1 and FIML methods. RMSEs do not assume negative values, which is why all bars start at zero and have a positive number associated with their height.

We can see that the FSEM1 and FSEM2 methods yield path coefficients that are, on aggregate, fairly similar to those generated by the FIML method. Of the two methods, FSEM1 and FSEM2, the one closest to FIML in terms of path coefficient estimates is the FSEM2 method. This is interesting, because the FSEM2 method can be seen as a "hybrid" method that incorporates elements of classic composite-based and modern factor-based SEM methods. As noted earlier, the FSEM2 method first estimates composites based on PLS Regression, and then uses those estimates to obtain factors employing the variation sharing algorithm (Kock, 2015b).

Figure 3 shows illustrative differences among loading estimated through the four methods. Similarly to the previous figure, four bars are shown; each representing the RMSE calculated based on individual loading differences involving a pair of methods matched for comparison purposes. The pairs of methods that are compared are presented in the same order as in the previous figure.

Figure 3: Differences among loadings (RMSEs)



The FSEM1 method yields loadings that are, on aggregate, fairly similar to those generated by the FIML method. The FSEM2 method, on the other hand, yields loadings that are, on aggregate, fairly similar to those generated by the PLSA method. Based on these results, it would be reasonable to argue that, if one were to conduct a measurement model assessment that is more compatible with covariance-based SEM, without using a classic covariance-based SEM method such as FIML, one should consider using the FSEM1 method.

Why should one employ a method such as FSEM1 instead of FIML? There are many reasons for that possible choice to be made. One is that the more modern FSEM1 method does not make any assumptions about data distribution (e.g., that the indicator data is normally distributed). Another reason is that the more modern FSEM1 method allows for the construction of fairly complex models, nearly always generating usable results – without the convergence problems often found with complex models in covariance-based SEM methods such as FIML.

But one of the most important reasons why a researcher may prefer to use a method such as FSEM1 instead of FIML is that FSEM1 generates latent variable scores, which can then be used in nonlinear analyses. In this respect, FSEM1 is like the FSEM2 and PLSA methods; all of these three methods generate latent variable scores during the estimation process. Of the three, FSEM1 and FSEM2 generate latent variable scores that minimize path coefficient bias. With latent variable scores, nonlinear multivariate data analysis tools such as WarpPLS can then be used in analyses that take into consideration possible curvilinear relationships among latent variables.

Discussion and concluding remarks

The gap between factor-based and composite-based SEM methods has until recently been a major barrier to methodological integration in the SEM realm. Recent methodological developments building on PLS, as well as related techniques and ideas, have significantly contributed to bridging this gap. To our knowledge at least one widely used PLS-SEM software tool, namely WarpPLS, comprehensively implements these developments.

A distinguishing characteristic of the factor-based SEM methods discussed here is that they build on classic PLS-SEM techniques as well as on more modern techniques. They estimate both factors and composites; with the factors being derived from the composites, and with those factors fully incorporating measurement error.

Given that factor-based SEM takes into account measurement error, and that measurement errors in the same model tend to be inter-correlated, factor-based SEM tends to correct the path coefficient attenuation bias often seen in classic PLS-SEM methods that rely solely on composites for estimation of SEM model parameters.

We compared 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). Our analyses suggest 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.

Acknowledgments

The author is the developer of the software WarpPLS, which has over 7,000 users in more than 33 different countries at the time of this writing, and moderator of the PLS-SEM e-mail distribution list. He is grateful to those users, and to the members of the PLS-SEM e-mail distribution list, for questions, comments, and discussions on topics related to the use of WarpPLS.

References

Kock, N. (2005). What is e-collaboration. *International Journal of e-Collaboration*, 1(1), 1-7.

Kock, N. (2008). E-collaboration and e-commerce in virtual worlds: The potential of Second Life and World of Warcraft. *International Journal of e-Collaboration*, 4(3), 1-13.

Kock, N. (2010). Using WarpPLS in e-collaboration studies: An overview of five main analysis steps. *International Journal of e-Collaboration*, 6(4), 1-11.

Kock, N. (2013). Using WarpPLS in e-collaboration studies: What if I have only one group and one condition? *International Journal of e-Collaboration*, 9(3), 1-12.

Kock, N. (2014). Advanced mediating effects tests, multi-group analyses, and measurement model assessments in PLS-based SEM. *International Journal of e-Collaboration*, 10(3), 1-13.

Kock, N. (2015a). *WarpPLS 5.0 User Manual*. Laredo, TX: ScriptWarp Systems.

Kock, N. (2015b). A note on how to conduct a factor-based PLS-SEM analysis. *International Journal of e-Collaboration*, 11(3), 1-9.

Kock, N. (2016). Non-normality propagation among latent variables and indicators in PLS-SEM simulations. *Journal of Modern Applied Statistical Methods*, 15(1), 299-315.

Kock, N., & Gaskins, L. (2014). The mediating role of voice and accountability in the relationship between Internet diffusion and government corruption in Latin America and Sub-Saharan Africa. *Information Technology for Development*, 20(1), 23-43.

Kock, N., & Lynn, G.S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, 13(7), 546-580.

Kock, N., & Mayfield, M. (2015). PLS-based SEM algorithms: The good neighbor assumption, collinearity, and nonlinearity. *Information Management and Business Review*, 7(2), 113-130.

Kock, N., & Verville, J. (2012). Exploring free questionnaire data with anchor variables: An illustration based on a study of IT in healthcare. *International Journal of Healthcare Information Systems and Informatics*, 7(1), 46-63.

Robert, C.P., & Casella, G. (2005). *Monte Carlo statistical methods*. New York, NY: Springer.

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, 48(2), 1-36.