Reliability assessment in SEM models with composites and factors: A modern perspective

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Abstract

This paper's focus is on reliability tests for both composite-based and factor-based analysis algorithms in structural equation modeling through partial least squares (PLS-SEM). We illustrate this analysis employing a widely used PLS-SEM software tool, WarpPLS. The results show the magnitude of differences between the two approaches, suggesting that the estimates of coefficients obtained using the factor-based approach are more conservative than those obtained using the corresponding composite-based approach.

Keywords: Structural Equation Modeling; Partial Least Squares; Reliability Test; Composite-Based; Factor-Based; WarpPLS.

Introduction

While composite-based and factor-based structural equation modeling have existed side by side for some time, there remains contention between the two forms of measurement with respect to reliability assessment. This contention leads to criticisms that PLS-based structural equation modeling (PLS-SEM) yields incorrect results, since it is a composite-based analysis method, as opposed to a factor-based analysis method. The factor-based proponents cite attenuation of path coefficients and overestimation of loadings, which underly the tendency to yield biased values for parameters (Kock, 2017).

In this study, we set out to investigate comparatively the performance of composite-based and factor-based SEM reliability tests to determine which of the two methods show more conservative estimates. We use WarpPLS version 7.0 (Kock, 2014; 2020a) to illustrate our analyses in this paper, which also demonstrates the ease in which this kind of comparison can be accomplished due to its many user-friendly yet advanced features (Amora, 2021; Hubona &

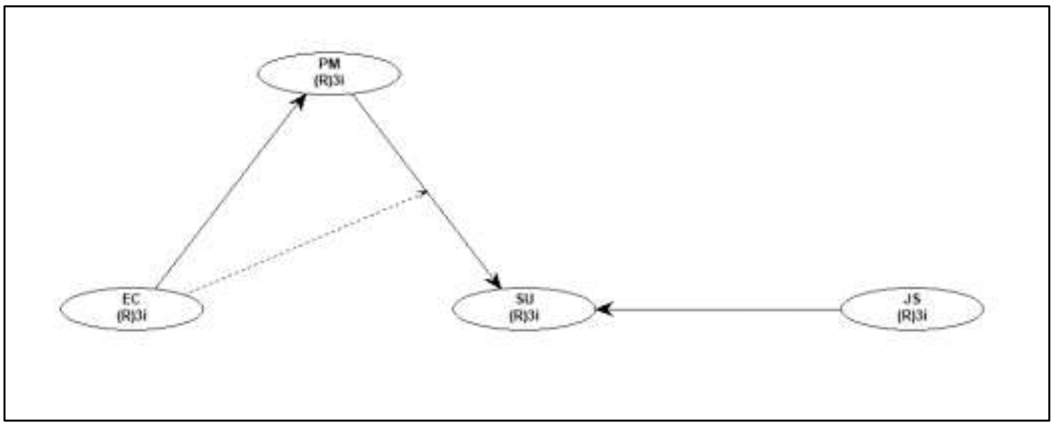
Belkhamza, 2021; Moqbel et al., 2020; Kock, 2020b; 2020c; 2020d; 2021a; 2021b; Morrow & Conger, 2021).

As it befits a tutorial, our discussion will progress in a straightforward manner to discuss the topic of interest: composite-based and factor-based SEM reliability tests. The base model for the study is presented in Figure 1. Subsequent figures present the results using both composite-based and factor-based SEM and their corresponding reliability tests.

Base model and data

We have used the sample e-collaboration moderation simulated dataset from the WarpPLS website. For the data collection, we follow steps used in previous studies, adopting a dataset generated from a Monte Carlo simulation (Robert & Casella, 2005; Kock, 2015b; Kock, 2016). The SEM model in Figure 1 illustrates the base model.

Figure 1: Base model used



Notes: Model notations used are the same as those utilized in Kock (2016; 2020c). EC = e-collaboration technology use; PM = project management techniques use; SU = project success; JS = job satisfaction; notation under latent variable acronym describes measurement approach and number of indicators, e.g., (R)3i = reflective measurement with 3 indicators.

Why is the reliability test needed?

The objective of assessing reliability is to establish how much of the variance in a model's results is due to variance in the original data or a result of certain errors in measurement, notably misunderstandings among respondents about the meaning of the question-statements used. Reliability, then, is the extent to which the results are produced under consistent conditions. Measurement data that is reliable is consistent from one analysis to another when repeated. Thus, a reliability test is needed to ensure that the collected data is reliable.

Why test with composite-based and factor-based methods?

We first obtain the results of the base model using two different methods: first, with the composite-based method and second, with the factor-based method. The composite-based method uses linear combinations of indicators to form variables that empirically represent the conceptual variables, whereas the factor-based method empirically represents the conceptual variables using common factors, consisting of only common variance that explains the covariation between their associated indicators. Figure 2 reports the composite-based results, and Figure 3 reports the factor-based results.

Figure 2: Composite-based results

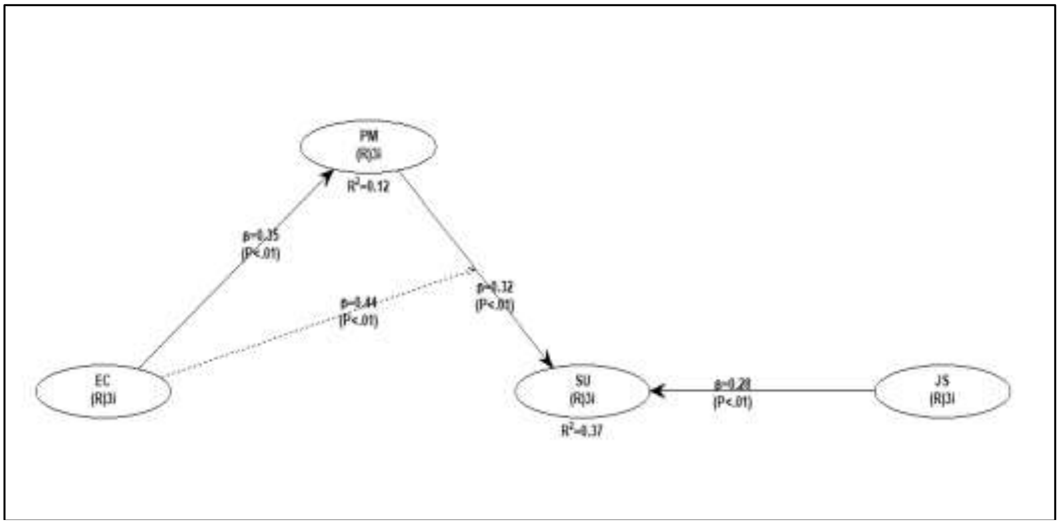
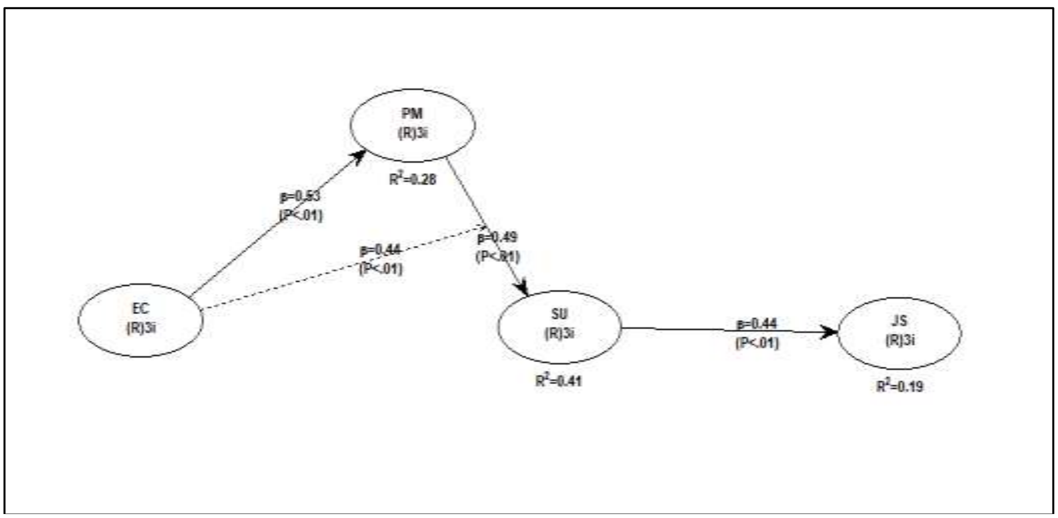


Figure 3: Factor-based results



Comparing composite-based and factor-based results

We then test the reliability of the models and compare the results. To obtain the composite-based or factor-based results, click on "Settings", then choose "View or change general settings". This setting is the same for composite-based and factor-based methods. Then for composite-based results, choose "PLS Regression", "Linear", and "Stable3".

For factor-based results, choose "Factor-Based PLS Type CFM3" from "Outer model analysis algorithm", Click "Save". Next, click on "Explore and then Explore additional coefficients and indices".

This step is the same for both methods. Lastly, choose "Reliabilities (extended set)" from the drop-down box. This step is the same for both methods. (See Figure 4 for composite-based results and Figure 5 for factor-based results).

Figure 4: Composite-based reliability results

Save Close Help

What to display?

Reliabilities (extended set)

Notes: here you can view additional coefficients and indices that are not available e what you want to display.

Reliabilities (extended set)
****

Outer model analysis algorithm: PLS Regression

Classic reliability coeffs.

	EC	PM	SU	JS	EC*PM
Composite reliability	0.813	0.820	0.811	0.821	1.000
Cronbach's alpha	0.656	0.671	0.650	0.673	1.000

Additional reliability coeffs.

	EC	PM	SU	JS	EC*PM
Dijkstra's PLSc reliability	0.661	0.673	0.652	0.690	1.000
True composite reliability	0.813	0.820	0.811	0.821	1.000
Factor reliability	0.813	0.820	0.811	0.821	1.000

Figure 5: Factor-based reliability results

Save Close Help

What to display?

Reliabilities (extended set)

Notes: here you can view additional coefficients and indices that are not available elsewhere in what you want to display.

Reliabilities (extended set)
****

Outer model analysis algorithm: Factor-Based PLS Type REG2

Classic reliability coeffs.

	EC	PM	SU	JS	EC*PM
Composite reliability	0.659	0.672	0.653	0.683	1.000
Cronbach's alpha	0.656	0.671	0.650	0.673	1.000

Additional reliability coeffs.

	EC	PM	SU	JS	EC*PM
Dijkstra's PLSc reliability	0.661	0.672	0.653	0.691	1.000
True composite reliability	0.812	0.820	0.811	0.821	1.000
Factor reliability	0.659	0.672	0.653	0.683	1.000

Comparison of the composite-based and factor-based reliability results

It is important to note that WarpPLS classifies the reliability coefficients (extended set) into two groupings. The first group is labeled "Classic Reliability Coefficients" and reports (a)

Composite Reliability and (b) Cronbach's Alpha. The second group is labeled "Additional Reliability Coefficients" and reports (a) Dijkstra's PLSc Reliability, (b) True Composite Reliability, and (c) Factor Reliability.

The Cronbach's Alpha values obtained in composite-based and factor-based methods are the same to the last decimal. Aside from the slight differences observed in the third decimals of the Dijkstra's PLSc and True Composite Reliability estimates, the coefficients were the same for the composite-based and factor-based algorithms. However, the composite and factor reliability coefficients are where we see a diversion of results between the two models, with the factor-based reliability results much lower when compared with the composite-based reliability results.

In composite-based reliability computations, the true estimates of the reliability coefficients are derived prior to the completion of the iterative estimation. However, under the factor-based reliability estimates, the reliability coefficients are arrived at upon the completion of the iterative process of estimation premised on the "true composites and factor estimates" (Kock, 2015a).

As a matter of distinction, researchers must take cognizance of these two focal reliability tests: composite reliability and factor reliability as distinct from the names of the algorithm under which they are estimated; composite-based and factor-based. As a tool, WarpPLS displays the results so that the researcher can follow the analysis step by step. This level of user-friendliness also brings clarification to these often-misconceived concepts, which we deem crucial to the success of researchers seeking to employ reliability tests to gain more in-depth insight for their studies.

Conclusion

A comparison of reliability assessment results found that Cronbach Alpha reliability results are the same due to the functions that are used in the calculation and are not affected by whether the analysis is composite-based or factor-based. Likewise, it was found that there is little to no difference between respective algorithms and the coefficients for the Dijkstra's PLSc and True Composite Reliability estimates. In this paper, we illustrated that factor-based reliability results are much lower than composite-based results. Therefore, the factor-based measurement of reliability will be the preferred choice if a more conservative view of the results is desired.

Acknowledgment

The authors are grateful to the editors of the journal, to Texas A&M International University doctoral students and, especially to Dr. Ned Kock for his scholarly guidance prior to submission of our manuscript to Data Analysis Perspectives Journal.

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