Methods showcase - Using PLSF-SEM in business communication research

Ned Kock

Full reference:

Kock, N. (2025). Methods showcase - Using PLSF-SEM in business communication research. *International Journal of Business Communication*, 62(1), 187-205.

Abstract

Structural equation modeling (SEM) is a data analysis method that is widely used in business communication research, as well as research in many other fields, when scholars need to test complex models with multiple outcomes, interactions, or operations across different situations. To date, however, researchers have had to choose between using covariance-based SEM, and dealing with convergence problems; or composite-based SEM, and facing serious methodological issues. This article describes a way to combine strong aspects of both SEM types through PLSF-SEM. By utilizing this novel method, empirical researchers can employ several of the same tests traditionally used in covariance-based SEM, as well as new tests that rely on latent variable estimates, in a succinct and scholarly way. PLSF-SEM builds on partial least squares (PLS) algorithms to generate correlation-preserving factors; the F refers to it being factor-based, as opposed to composite-based. A primer on the use of PLSF-SEM in business communication research is provided, based on an illustrative model inspired by motivating language theory, and where simulated data was analyzed with the software WarpPLS.

Keywords: Factors; Composites; Exogenous Variables; Endogenous Variables; Structural Equation Modeling; Partial Least Squares; WarpPLS.

Introduction

Business communication research has become increasing complex over the past decades. To capture this complexity business communication researchers have increasingly turned to more sophisticated methods – with structural equation modeling (SEM) being one of the most advanced methods used for cross-sectional analyses (Alikaj & Hanke, forthcoming; Charoensukmongkol & Phungsoonthorn, 2022). SEM allows a researcher to test both a structural model and a measurement model, simultaneously (Kock, 2023). The structural model, which aims at summarizing elements of a theoretical model, usually involves a set of variables – called latent variables (LVs) – that cannot be measured directly without error. At the same time, SEM can test causal relationships among these LVs (represented through arrows) in the same way a regression or path analysis can. The measurement model involves variables called indicators that measure LVs with error, as well as LV-indicator associations; where indicators are commonly quantified as responses to question-statements on Likert-type scales in questionnaires.

Partial least squares path modeling (PLS-PM) has emerged recently as an intended alternative to the more established covariance-based (CB) approach to SEM (Kock, 2019a; 2019b; 2023). Examples of widely used software tools that implement these methods are WarpPLS, for PLS-PM, and Amos, for CB-SEM. PLS-PM has one major advantage over CB-SEM that makes the method attractive to business communication researchers – it almost always converges to a solution. While this advantage may seem esoteric, it gives the business communication researcher the opportunity to model highly complex models with multiple independent, dependent, moderating, and mediating variables.

As most business communication researchers understand, communication presents complex processes that can involve multiple, interacting relationships between constructs. If we ignore this complexity, we risk simplifying communication processes to a point where they have no application in the real world. But this complexity also makes it difficult to find a suitable analysis method. With CB-SEM, models that have too much complexity will often fail to provide any viable solution. Software tools implementing CB-SEM will simply not have the capacity to analyze a complex model we need to use to reflect reality. PLS-PM on the other hand, can handle a model of almost any level of complexity.

The main disadvantage of PLS-PM is that it approximates LVs through composites, instead of factors, which leads to biased parameters. This disadvantage tends to be particularly problematic with effects that do not exist at the population level, which tend to be estimated as nonzero effects by PLS-PM, leading to unacceptably high incidences of type I errors (Kock, 2019a; 2019b). This has spurred vociferous criticism (Kock, 2019a; 2023), and calls for automatic desk rejections by journal editors of articles employing PLS-PM.

The potential of biased parameters and increased type I errors creates special problems for business communication researchers due to the field's focus on using research for practical solutions. Biased parameters may also lead to the magnitude of relationships being misestimated, so that what may appear to be a strong relationship being weak or vice-versa. These misestimations could lead to wrong managerial decisions or policy implementations. The increase in type I errors can lead researchers to believe relationships exist when they do not, again potentially leading to costly training on communication methods that do not work.

Proponents of the use of PLS-PM for SEM have sought several ways to overcome these limitations. They have proposed, over the past several years, new terminology and a variety of new tests and criteria aimed at working around the problems stemming from approximating LVs through composites, without actually addressing the main cause of those problems. This has left users with a bewildering array of ad hoc tests, which have drawn even stronger criticism. Examples are the heterotrait-monotrait (HTMT), HTMT2, PLSpredict, confirmatory tetrad, importance-performance, and data segmentation tests, among others. Empirical researchers are caught in the middle, with increasingly louder calls to ban PLS-PM from major journals, and with a bewildering array of tests to report in order to legitimize their use of PLS-PM. The need to report many tests leads to long papers with unfocused methodological sections. Generally, review panels do not *like* to start with long papers, because papers tend to grow larger with revisions and resubmissions. Thus, other things being equal, long papers are more likely to be rejected.

A new form of SEM that builds on PLS algorithms to generate correlation-preserving factors (PLSF-SEM) has been recently developed (Kock, 2019a; 2019b). Through it, empirical researchers can use several of the same tests traditionally used in CB-SEM, as well as new tests that rely on LV estimates (which are typically not available from CB-SEM), in a succinct and scholarly way. As of this writing, PLSF-SEM is implemented through the software WarpPLS (Kock, 2022a), with other implementations (including R packages) on the way. PLSF-SEM is designed for SEM analyses where LVs are modeled as factors, and not as composites. It is, like CB-SEM, statistically consistent, asymptotically converging to the true values of parameters (e.g., loadings and path coefficients) as sample sizes increase. Also, PLSF-SEM presents greater statistical efficiency than CB-SEM, converging to the true values *faster*; i.e., with smaller sample sizes (Kock, 2019a). In this paper, we provide a discussion on how PLSF-SEM can be used in business communication research, in a fashion that is both succinct and scholarly.

Some disclosures

Citations. This journal is arguably the premier scholarly outlet in the world covering business communication and related research. It deserves from authors the highest standards of scholarship and integrity. As noted above, we are fairly critical of the ways in which proponents of the use of PLS-PM for SEM sought to legitimize the method; see our comment on: HTMT, HTMT2, PLSpredict, confirmatory tetrad, importance-performance, and data segmentation. However, this is a scholarly viewpoint, as we also believe that those proponents are well-intentioned. Given this, and to affirm our commitment to integrity, we avoided citations that would give the impression that we wanted to attack individuals, publication outlets, or publishers. Therefore, the citations below should be seen as recognition of well-intentioned work on our part, and not as targeted criticism.

HTMT – Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43, 115-135.

HTMT2 – Roemer, E., Schuberth, F., & Henseler, J. (2021). HTMT2–an improved criterion for assessing discriminant validity in structural equation modeling. Industrial Management & Data Systems, 121(12), 2637-2650.

PLSpredict – Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. European Journal of Marketing, 53(11), 2322-2347.

Confirmatory tetrad – Gudergan, S. P., Ringle, C. M., Wende, S., & Will, A. (2008). Confirmatory tetrad analysis in PLS path modeling. Journal of Business Research, 61(12), 1238-1249.

Importance-performance – Hauff, S., Richter, N. F., Sarstedt, M., & Ringle, C. M. (2024). Importance and performance in PLS-SEM and NCA: Introducing the combined importance-performance map analysis (cIPMA). Journal of Retailing and Consumer Services, 78, 103723.

Data segmentation – 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.

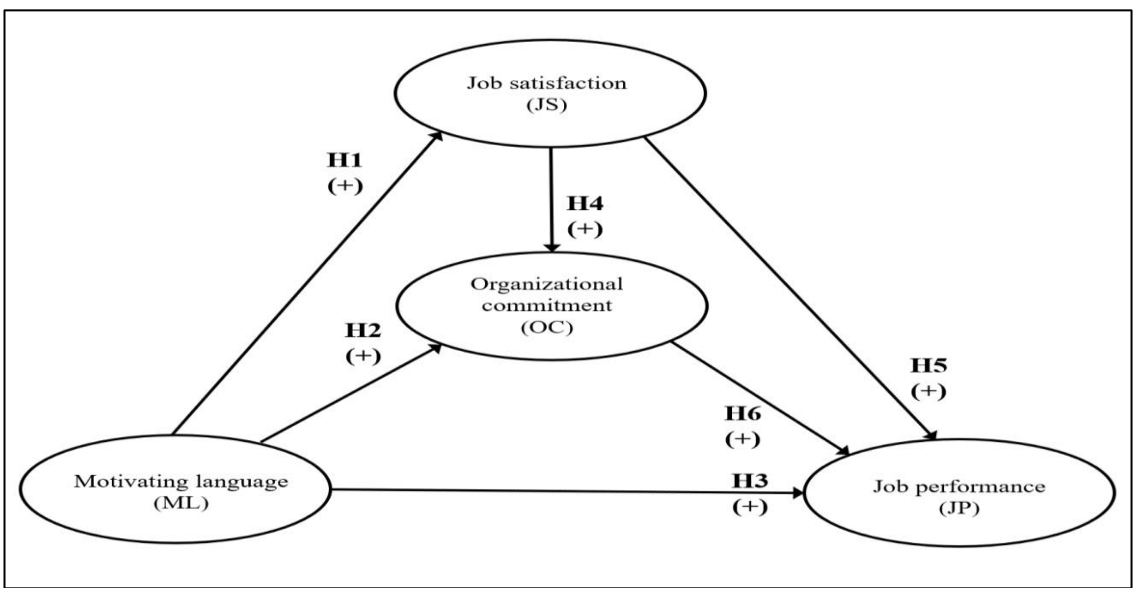
Consistent PLS. As noted by Kock (2019a), the new PLSF-SEM method relies on the consistent PLS technique, developed in the 1980s by one of the greatest mathematical statisticians to have ever lived, the late Theo Dijkstra (Huang, 2013). The PLSF-SEM method starts with a PLS-PM analysis employing the centroid scheme. Using the weights generated by this analysis, two equations from the consistent PLS technique (see, e.g.: Dijkstra & Schermelleh-Engel, 2014) are used to produce consistent estimates of LV reliabilities and LV-indicator loadings. The PLSF-SEM method then proceeds in a stochastic fashion to a composite estimation stage employing the Moore–Penrose pseudoinverse calculation procedure, which is then followed by a factor-estimation stage employing a novel variation sharing technique, and finally by a full parameter estimation stage implementing the two-stage least squares procedure utilizing stochastic instrumental variables. Consistent PLS is a small but important element of PLSF-SEM. We have previously developed a version of PLSF-SEM that does not employ the consistent PLS technique, and it seems to perform very well, but primarily when LV-indicator loadings are relatively homogeneous (Kock, 2015a).

WarpPLS. This article has extensively used the commercial WarpPLS software in examples of how to utilize PLSF-SEM. As stated in the article, this software has been developed by the author. The author had to rely on WarpPLS so extensively for the examples because – at the time of the article's writing – the software provides the only implementation of the discussed statistical method. However, other researchers are currently working on implementing the method through different software resources (including such open-source statistical software as R). The author regularly announces such developments on his web site (warppls.com) and will provide links to these implementations as they become available.

Illustrative Model

The illustrative model shown in Figure 1 is used in our discussion on how PLSF-SEM can be employed in business communication research. The model contains one exogenous LV, namely motivating language (ML); and three endogenous LVs, which are job satisfaction (JS), organizational commitment (OC) and job performance (JP). Exogenous LVs have no LVs pointing at them. Endogenous LVs are those that are pointed at by at least one other LV.

Figure 1: Illustrative model



Notes: the model has one exogenous LV: motivating language (ML); and three endogenous LVs: job satisfaction (JS), organizational commitment (OC), and job performance (JP).

All LVs in our model are assumed to be measured reflectively. That is, redundant question-statements of the type *I like my job* and *My job fulfills me* were assumed to have been used (in this example, for JS); as opposed to non-redundant question statements of the type *I like my boss* and *I like my office equipment*. The latter would characterize formative measurement, whose appropriate coverage would be outside the scope of this paper.

The model is consistent with motivating language theory (Mayfield & Mayfield, 2017), a seminal theoretical framework widely used in business communication research. There are 6 hypotheses to be tested in our illustrative model; such tests envisioned as being based on structural model results. These are primarily the path coefficients for the arrows among LVs, which can be found to be statistically significant or nonsignificant. In scientific writing, the word *nonsignificant* is preferred over *insignificant*; the latter usually implies lack of importance, without statistical connotations.

Our past experience writing papers summarizing empirical studies employing PLSF-SEM suggests that authors should aim for manuscripts with 6,000 to 7,000 words for initial submissions to most selective journals. Generally speaking, papers much larger than this would not be well received by review panels. The review process for selective journals, such as this, is likely to significantly increase the word count of manuscripts (e.g., from 6,000 to 10,000) as revisions and resubmissions take place.

Model complexity tends to be correlated with word count. Typically, an empirical study with 5 to 9 hypotheses (the magical number 7, plus or minus 2) will be amenable to succinct reporting with 6,000 to 7,000 words. Researchers desiring to test more complex models may want to consider splitting the reporting into two or more papers, each with 5 to 9 hypotheses. A greater number of hypotheses would tend to lead to not only longer theoretical background sections, but also longer methods and results sections.

As with the figure showing the model with main structural results, presented later in this paper, it is generally *not* recommended to use model screen shots taken directly from the WarpPLS software (or other SEM software) in papers summarizing empirical studies. The website warppls.com contains samples of PowerPoint files with the symbols typically used in models showing hypotheses and corresponding structural results. These can be used to create figures that will then be imported into a Word file, via an intermediate figure-editing software (e.g., Paint).

Three Key Methodological Sections

Here we discuss three key methodological sections, related to data collection, measurement model assessment, and reporting of model indices and structural results. These sections form the foundation of our recommendation for both succinct and scholarly methodological reporting by researchers employing the PLSF-SEM method. They are envisioned as being sections, not subsections (as presented here), of empirical papers.

Data Collection

In our illustrative example, the analyses were based on a simulated dataset, created through the Monte Carlo method (Kock, 2016). The simulated dataset was created with a size of 500, based on the illustrative model. Researchers analyzing empirical samples should provide a discussion of their data collection here, as well as their prospective minimum sample size requirements estimation (see below). For example, one could say that 500 questionnaires were collected, and that the questionnaires were completed by respondents from the USA. Details on questionnaire administration, respondents' demographics, and response rates should also be provided here.

Let us assume that theory and past empirical research suggest that the minimum absolute path coefficient associated with a *real* (i.e., nonzero at the population level) effect in our model is 0.147. Given this, we should conduct a prospective statistical power analysis to establish the minimum sample size required. Employing the inverse square root and gamma-exponential methods (Kock, 2023; Kock & Hadaya, 2018) with the significance level set at 0.05, the power level set at 0.8, and the minimum expected absolute path coefficient in the model set at 0.147, we obtained minimum required sample size estimates of 287 and 273, respectively. Since our sample size is 500, it handily meets minimum sample size requirements in our example, because 500 is much higher than the more conservative estimate of 287 yielded by the inverse square root method. Appendix A shows how this estimation can be conducted with WarpPLS.

One of the most controversial issues involving proponents of the use of PLS-PM for SEM and their detractors (mostly in the CB-SEM camp) has been that of minimum sample size estimation, for which the *10-times rule* has been a favorite in PLS-PM studies due to its ease of use, even though it tends to yield grossly imprecise underestimations in many cases (Kock, 2023). According to this rule, the minimum required sample size is the smallest integer equal to or greater than 10 times the maximum number of structural or measurement model links pointing at any LV in the model, which in our case would be 30 since all of our LVs are reflectively measured and the maximum number of structural links is 3 (pointing at JP). This number (i.e., 30) would have been a gross underestimation in our case (for a discussion, see: Kock & Hadaya, 2018). The inverse square root and gamma-exponential methods were developed to address this problematic state of affairs, and are the methods recommended in PLSF-SEM for statistical power and minimum sample size estimation.

Measurement Model Assessment

Good measurement model quality is a pre-condition for hypothesis testing employing structural model coefficients. A succinct and scholarly measurement model assessment in PLSF-SEM should cover the following elements: convergent validity, discriminant validity, reliability, common method bias, and multivariate normality. The first four are also typical in CB-SEM assessments. The fifth, multivariate normality, is aimed at providing a compelling justification for the use of PLSF-SEM (instead of CB-SEM or other parametric approaches), since PLSF-SEM is a nonparametric SEM method that does not assume that LVs (or indicators) are normally distributed (Kock, 2016). Non-normality is often a problem in CB-SEM.

Convergent validity. Table 1 shows all loadings and cross-loadings among indicators and LVs in our model, which provide the basis on which convergent validity can be assessed. Appendix B shows how these loadings and cross-loadings would look in WarpPLS. As we can see, all loadings are greater than 0.5, suggesting good convergent validity. That is, they suggest that the respondents appeared to have understood the question-statements associated with each of the LVs in the same way as the designers of the questionnaire did. Loadings are unrotated and cross-loadings are oblique-rotated. Cross-loadings are oblique-rotated because LVs are not expected to be orthogonal. It is important to include oblique-rotated cross-loadings in this type of assessment; these tend to be lower than unrotated cross-loadings. Oblique-rotated cross-loadings > 0.5 are warning signs, indicating possible measurement model problems.

Table 1: Loadings and cross-loadings for LVs

	ML	JS	OC	JP
ML1	(0.761)	-0.015	-0.060	-0.042
ML2	(0.788)	0.009	-0.100	-0.028
ML3	(0.751)	-0.076	-0.032	-0.060
JS1	0.085	(0.766)	-0.188	-0.066
JS2	-0.097	(0.756)	-0.020	-0.066
JS3	-0.071	(0.760)	0.001	-0.111
OC1	-0.070	-0.125	(0.747)	-0.065
OC2	-0.052	-0.028	(0.760)	-0.167
OC3	-0.078	-0.059	(0.790)	-0.047
JP1	0.075	-0.104	-0.213	(0.769)
JP2	-0.104	0.007	-0.087	(0.758)
JP3	-0.098	-0.137	0.023	(0.775)

Notes: Loadings are unrotated and cross-loadings are oblique-rotated. Loadings shown within parentheses in shaded cells. Loadings > 0.5 suggest good convergent validity. Oblique-rotated cross-loadings > 0.5 would be warnings.

As noted earlier, proponents of the use of composite-based PLS-PM for SEM have offered new criteria that are purported to work around the problems stemming from approximating LVs through composites. One such criterion is the adoption of a higher threshold for loadings (e.g., 0.7) to be employed in the assessment of convergent validity. The reason for this is that loadings are overestimated by PLS-PM, yielding higher values than PLSF-SEM (and also CB-SEM). Even though all of the loadings are greater than 0.7 in our example, we recommend that the threshold of 0.5 be used with PLSF-SEM, since this method does not overestimate loadings. Adopting a higher threshold could lead to methodological decisions that would detract from the overall measurement model quality; e.g., removal of what appear to be offending indicators could lead to an artificial decrease in reliability.

Discriminant validity. Table 2 shows correlations and square roots for average variances extracted (AVEs) for our main model's LVs, which allow for discriminant validity to be assessed. As we can see, all square roots of AVEs were greater than the correlations in the same columns, suggesting good discriminant validity. That is, the respondents seemed to have not mistaken question-statements as associated with LVs that were not the ones intended by the designers of the questionnaire. This validation approach, generally known as the Fornell-Larcker criterion test, is one of the most popular in SEM in general.

Table 2: Correlations and square roots of AVEs for LVs

	ML	**JS**	**OC**	**JP**
ML	(0.767)	0.627	0.722	0.678
JS	0.627	(0.761)	0.756	0.758
OC	0.722	0.756	(0.766)	0.763
JP	0.678	0.758	0.763	(0.767)

Notes: Square roots of AVEs show along diagonal within parentheses in shaded cells. Square roots of AVEs greater than the correlations in the same column suggest good discriminant validity.

Again, since composite-based PLS-PM yields biased estimates of AVEs and LV correlations, proponents of the use of PLS-PM for SEM have offered new ad hoc tests that are purported to work around the problems stemming from approximating LVs through composites. Two such tests build on the HTMT and HTMT2 ratios (mentioned earlier); these tests are not needed in PLSF-SEM. Nevertheless, WarpPLS provides the necessary coefficients for these tests to be conducted, if review panels ask for them. The sub-option *Discriminant validity coefficients (extended set)*, under the WarpPLS menu option *Explore additional coefficients and indices*, can be used to obtain those coefficients. WarpPLS also implements many other tests used by proponents of the use of PLS-PM in SEM, which are made available in the software for completeness.

Reliability, common method bias, and multivariate normality. Table 3 shows selected LV coefficients for our main model's LVs. These coefficients are available from two main areas in WarpPLS: (a) the menu sub-option *View latent variable coefficients*, under the *View/save analysis results* button; and (b) the menu sub-option *Explore additional coefficients and indices*, under the *Explore* menu option. They are used for tests of reliability, common method bias, and multivariate normality.

Table 3: LV coefficients

	ML	JS	OC	JP
Factor reliability	0.811	0.805	0.810	0.811
Cronbach's alpha	0.810	0.805	0.810	0.811
Full collinearity VIF	2.235	2.803	3.754	3.484
Jarque-Bera test of normality	No	No	No	No
Robust Jarque-Bera test of normality	No	No	No	No

Notes: Composite reliabilities and Cronbach's alphas > 0.6 suggest good reliability. FCVIFs < 10 suggest no common method bias. Multivariate non-normality, indicated by the Jarque-Bera test and its robust variation, provide support for the use of the non-parametric PLSF-SEM method.

The factor reliabilities and Cronbach's alphas were all greater than 0.6, suggesting good reliability. As we can see, these two reliability measures are almost identical in value in our example. This usually happens when loadings are homogenous, otherwise factor reliabilities would tend to be higher than Cronbach's alphas. In such cases, it is recommended that factor reliabilities be compared against the threshold of 0.6, but not Cronbach's alphas, because the latter would tend to underestimate the reliabilities (with respect to the true values). The PLS-PM equivalent, composite reliabilities, typically overestimate reliabilities; which has prompted proponents of the use of PLS-PM for SEM to offer higher thresholds (e.g., 0.7) to make up for the overestimation. Good reliability generally means that the respondents appeared to have understood the question-statements used to measure each LV in the same way among themselves (i.e., the respondents).

All full collinearity variance inflation factors (FCVIFs) were significantly lower than 10, suggesting no common method bias. This threshold of 10 is recommended for PLSF-SEM. The threshold of 3.3, employed in a widely used PLS-PM version of this test (Kock, 2015; Kock & Lynn, 2012), is too low for PLSF-SEM. The difference is due to PLS-PM's underestimation of FCVIFs with respect to the true values (Kock, 2023). This full collinearity test in PLSF-SEM, with a threshold of 10, is more sensitive to common method bias than Harman's single factor test employing PLSF-SEM (Kock, 2021a). Nevertheless, absence of common method bias may be further assessed through Harman’s test, which can be easily implemented with WarpPLS (see: Kock, 2021a). If common method bias is found to exist, the common structural variation reduction technique can be employed with WarpPLS to ameliorate the situation (Kock, 2021b), even though this technique does not extract common method variation from indicators (only from LVs, hence its name).

In our example, multivariate non-normality was indicated, by the Jarque-Bera test and its robust variation (the robust Jarque-Bera test of normality), as existing in all of the LVs in our model. This provides support for our use of PLSF-SEM, and is recommended to be reported in empirical studies employing this method. As previously noted, PLSF-SEM is a factor-based nonparametric SEM method that does not assume multivariate normality. This is in contrast to CB-SEM, which is a parametric method that *does* assume multivariate normality. In our experience assisting WarpPLS users to conduct SEM analyses over many years, where we usually test for multivariate normality, it seems that virtually all datasets employed in SEM analyses fail meet the assumption of multivariate normality.

Model Indices and Structural Results

The use of the PLSF-SEM method allows empirical researchers to assess the quality of their models via various structural and measurement model indices, most of which cannot be calculated in CB-SEM and would be biased with PLS-PM. Table 4 shows the quality indices calculated for our model. The sub-option *Model fit and quality indices (extended set),* under the WarpPLS menu option *Explore additional coefficients and indices,* can be used to obtain the values of these indices, after the SEM analysis of an empirical dataset is conducted.

Table 4: Model quality indices

Index	Value	Interpretation
Average R-squared (ARS)	0.593	P<0.001
Average adjusted R-squared (AARS)	0.592	P<0.001
Average block VIF (AVIF)	2.187	acceptable if <= 5, ideally <= 3.3
Average full collinearity VIF (AFVIF)	3.069	acceptable if <= 5, ideally <= 3.3
Tenenhaus GoF (GoF)	0.589	small >= 0.1, medium >= 0.25, large >= 0.36
Simpson's paradox ratio (SPR)	1.000	acceptable if >= 0.7
R-squared contribution ratio (RSCR)	1.000	acceptable if >= 0.9
Standardized root mean squared residual (SRMR)	0.039	acceptable if <= 0.1
Standardized mean absolute residual (SMAR)	0.030	acceptable if <= 0.1

Both the average R-squared (ARS) and the average adjusted R-squared (AARS) suggest significant levels of variance explained in the model's endogenous variables. The variance inflation factor (VIF) indices, namely the average block VIF (AVIF) and average full collinearity VIF (AFVIF), were both below 3.3, suggesting low levels of vertical and lateral collinearity (Kock, 2014; Kock & Lynn, 2012). Finding low levels of vertical and lateral collinearity essentially means that the LVs used in the model appeared to measure different underlying constructs. The low values of the AVIF and AFVIF indices also suggest that the model is generally free from common method bias, serving as model-wide complements to the FCVIFs calculated for individual LVs that were presented earlier (Kock, 2015; Kock & Lynn, 2012).

The Tenenhaus GoF (GoF), named in honor of Michel Tenenhaus, suggests a large level of goodness-of-fit between the model and the data (Kock, 2014; 2022a). The next two rows in the table provide the values of the following causality assessment indices (Kock, 2022b): Simpson's paradox ratio (SPR) and R-squared contribution ratio (RSCR). Those values suggest that the model is generally sound in terms of its causality assumptions. That is, the directions of causality implied by the links connecting the variables in the model appear to be correct.

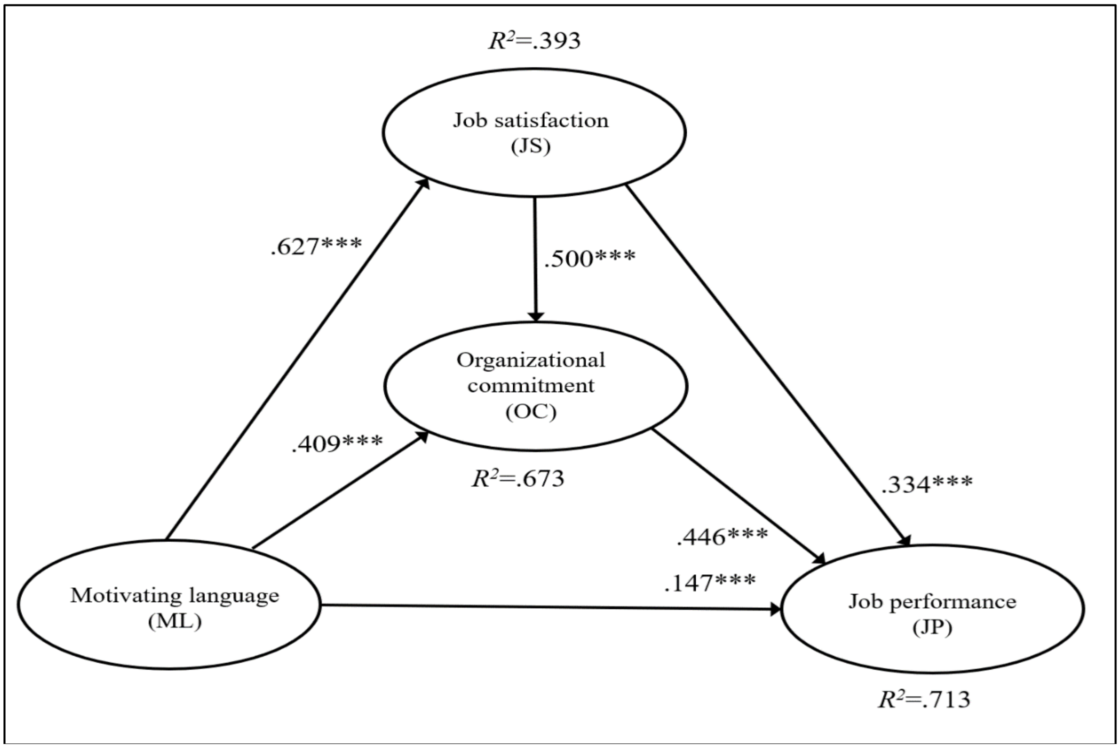
The last two rows of the table provide the values of the following indices, which are gauges of the difference between the model-implied and actual indicator correlation matrices: Standardized root mean squared residual (SRMR) and standardized mean absolute residual (SMAR). Measures of the difference between the model-implied and actual indicator correlation matrices are key ingredients of CB-SEM. They are highly recommended in PLSF-SEM (Kock, 2020), because they provide an important *global* (i.e., broad) measure of fit between the model and the data. In our example, these indices yielded values of 0.039 and 0.030 respectively, both well below the threshold of 0.1, thus suggesting that there was a good fit between the model and the data (Kock, 2020).

Figure 2 shows the main structural model results of our analyses, in the form of direct effects and R-squared coefficients. If moderating effects were present, they would also be summarized here. The same is true for the effects of control variables, if those were included. Often studies control for the effects of several demographic variables, which could have biased some of the results if omitted from the model. These may be included in WarpPLS models through single-indicator LVs pointing at endogenous LVs that are expected to share variation with the underlying control variables.

The path coefficients and respective P values for the causal links referring to direct effects were: ML > JS (β=0.627, P<0.001), ML > OC (β=0.409, P<0.001), ML > JP (β=0.147, P<0.001), JS > OC (β=0.500, P<0.001), JS > JP (β=0.334, P<0.001), and OC > JP (β=-0.446, P<0.001). The individual R-squared coefficients associated with each of the endogenous LVs suggest considerable levels of variance explained in those variables. Those R-squared coefficients would typically be the same with CB-SEM and much lower with PLS-PM. R-squared coefficients can be seen as measures of combined effect sizes. And effect sizes > 0.15 and > 0.35 are considered to be medium and large, respectively (Cohen, 1988). Thus, R-squared values > 0.15 and > 0.35

should be considered medium and large, respectively, in business communication research; as well as in behavioral research in general.

Figure 2: Structural model results



Notes: results obtained from the analysis of data generated via the Monte Carlo method; all path coefficients significant at the P < 0.001 level; if that were not the case, the superscript notation would be as follows; *** = significant at the P < 0.001 level; ** = significant at the P < 0.01 level; * = significant at the P < 0.05 level; ^{NS} = nonsignificant.

As noted earlier, the results shown are based on a simulated dataset, created through the Monte Carlo method (Kock, 2016); the simulated dataset was created with a size of 500, based on the illustrative model. All path coefficients turned out to be significant at the P < 0.001 level. This is in part due to the sample size, as P values are very sensitive to sample sizes. If that were not the case, the recommended superscript notation used would have been as follows: *** = significant at the P < 0.001 level; ** = significant at the P < 0.01 level; * = significant at the P < 0.05 level; NS = nonsignificant.

Appendix C shows how the illustrative model would look in WarpPLS. Again, it is generally not recommended to use model screen shots taken directly from the software in papers summarizing empirical studies. A possible exception to this general rule of thumb would be methodological papers like this, but arguably only when these papers are published in tool-specific journals (e.g., the *Data Analysis Perspectives Journal*).

The outer (i.e., measurement) model analysis algorithm setting in WarpPLS used to generate the results using PLSF-SEM in our illustrative analysis was *Factor-Based PLS Type CFM3*. Like CB-SEM algorithms, this algorithm is factor-based and fully compatible with common factor model assumptions (Kock, 2019a; 2019b), which form the foundation on which SEM in general rests. The inner (i.e., structural) model analysis algorithm used was *Linear*. This algorithm does not perform any warping of relationships (an important feature of WarpPLS, not covered here). Both outer and inner model algorithms are fully compatible with the way in which the simulated data was created via the Monte Carlo method.

Discussion and Conclusion

The three key methodological sections that have been just discussed form the foundation of our recommendation for both succinct and scholarly methodological reporting by researchers employing the PLSF-SEM method. We would also recommend a table summarizing the support for the hypotheses based on the results, as the core of a discussion section, to be included in papers after the three methodological sections. Table 5 is an example based on our illustrative model and related analyses.

Table 5: Support for the hypotheses based on the results

Hypothesis	Supported?
H1: Motivating language use is positively associated with job satisfaction.	Yes
H2: Motivating language use is positively associated with organizational commitment.	Yes
H3: Motivating language use is positively associated with job performance.	Yes
H4: Job satisfaction is positively associated with organizational commitment.	Yes
H5: Job satisfaction is positively associated with job performance.	Yes
H6: Organizational commitment is positively associated with job performance.	Yes

One important consideration should be made regarding the hypothesis *Motivating language use is positively associated with job performance*. The path coefficient for the corresponding link was found to be positive and statistically significant: ML > JP (β=0.147, P<0.001). However, if that were not the case, one could hardly conclude that motivating language use had no positive effect on job performance, because the total effect could have been positive. The β=0.147 refers to the effect for the link ML > JP after controlling for the competing effects of job satisfaction and organizational commitment on job performance.

Therefore, the ML > JP hypothesis could be re-worded as follows, for clarity: *Motivating language use is positively associated with job performance, after controlling for the effects of job satisfaction and organizational commitment*. Alternatively, that hypothesis could be replaced with a different one: *The effect of motivating language use on job performance is only partially mediated by job satisfaction and organizational commitment*. Full mediation would be associated with a nonsignificant path coefficient for ML > JP.

As it can be seen, we employed the term *motivating language use*, instead of simply *motivating language*. This is an instance of minor liberties that can be taken by researchers if they feel that particular hypothetical formulations may help readers better understand what they are hypothesizing and testing. A similar variation could be to use something like: *An increase in motivating language use is associated with an increase in job satisfaction*; instead of: *Motivating* *language use is positively associated with job satisfaction*. These essentially mean the same thing. More statistically sound but difficult to understand formulations, such as those building on null hypotheses, are generally discouraged. After all, it is commonly understood that hypotheses can never be proven through empirical research, only supported or not supported.

It should be noted that the word *perceived* is nowhere to be found in our hypothesis formulation. This is by design, not an oversight. In factor-based SEM methods, LVs are measured indirectly and with error via question-statements, which themselves (i.e., the question-statements) capture perceptions. In PLSF-SEM, perception-based indicators are then aggregated, together with a measurement residual, to produce LV scores that quantify the mental constructs that refer to the LVs.

That is, in PLSF-SEM perception-based data is used to produce estimates of the mental constructs that gave rise to the quantified perceptions. It is reasonable to assume, conceptually, that this is also true for other factor-based SEM approaches like CB-SEM, even though in CB-SEM parameters are estimated without aggregation of indicators into LVs. However, we cannot necessarily say the same for PLS-PM. The reason is that composites do not conform well with the idea of measurement with error. In LVs approximated via composites, the indicators explain 100 percent of the variance in the LV, with no room for a measurement residual (Kock, 2019b; 2023).

Given this, if the PLSF-SEM method is used, arguably the constructs should not be referred to as *perceived*, for one of two main reasons, depending on perspective. One reason, which we do not entirely agree with, is that it would be redundant to do so. The other, which is diametrically opposed and more in line with our view, is that the underlying constructs are something other than the perceptions that are used to measure them, at least until they are measured as perceptions (with error) and subsequently quantified as LVs. Either way, if the PLSF-SEM method is used, a hypothesis should not be worded as: *Perceived motivating language use is positively associated with perceived job satisfaction*. In other words, in PLSF-SEM one does not test the effects of perceptions on perceptions. One tests the effect of LVs on LVs, where the LVs are quantifications of entities that temporally precede perceptions – mental constructs.

We hope that this paper will be useful to business communication researchers employing PLSF-SEM. Other topics related to PLSF-SEM that are beyond the scope of this paper are covered in various documents and videos available from warppls.com. Among them are topics relevant in the context of SEM in general such as the operationalization of control variables, indirect and total effects, estimation and use of effect sizes, modeling and assessment of moderating effects, moderated mediation effects, full latent growth analyses, missing data imputation, multilevel analyses, use of logistic regression with certain endogenous variables, common structural variation removal, nonlinear relationships identification and modeling, testing of competing linear and nonlinear relationships, modeling and testing of reciprocal relationships, and endogeneity assessment and control.

Acknowledgments

The author is the developer of the software WarpPLS. He is grateful to WarpPLS users for questions, comments, discussions, and continued use. The author is also grateful to the Editors, Milton and Jackie Mayfield, for their invaluable comments and suggestions. This article contains revised text, originally written by the author, from a recent edition of the WarpPLS User Manual.

References

Alikaj, A., & Hanke, D. (forthcoming). An examination of the link between leader motivating language and follower interactional justice. *International Journal of Business Communication*.

Charoensukmongkol, P., & Phungsoonthorn, T. (2022). The interaction effect of crisis communication and social support on the emotional exhaustion of university employees during the COVID-19 crisis. *International Journal of Business Communication*, 59(2), 269-286.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Hillsdale, NJ: Lawrence Erlbaum.

Dijkstra, T.K., & Schermelleh-Engel, K. (2014). Consistent partial least squares for nonlinear structural equation models. *Psychometrika*, 79(4), 585-604.

Huang, W. (2013). *PLSe: Efficient estimators and tests for partial least squares*. Los Angeles, CA: University of California. (Doctoral dissertation.)

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

Kock, N. (2015b). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1-10.

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. (2019a). From composites to factors: Bridging the gap between PLS and covariance-based structural equation modeling. *Information Systems Journal*, 29(3), 674-706.

Kock, N. (2019b). Factor-based structural equation modeling with WarpPLS. *Australasian Marketing Journal*, 27(1), 57-63.

Kock, N. (2020). Using indicator correlation fit indices in PLS-SEM: Selecting the algorithm with the best fit. *Data Analysis Perspectives Journal*, 1(4), 1-4.

Kock, N. (2021a). Harman's single factor test in PLS-SEM: Checking for common method bias. *Data Analysis Perspectives Journal*, 2(2), 1-6.

Kock, N. (2021b). Common structural variation reduction in PLS-SEM: Replacement analytic composites and the one fourth rule. *Data Analysis Perspectives Journal*, 2(5), 1-6.

Kock, N. (2022a). *WarpPLS User Manual: Version 8.0*. Laredo, TX: ScriptWarp Systems.

Kock, N. (2022b). Using causality assessment indices in PLS-SEM. *Data Analysis Perspectives Journal*, 3(5), 1-6.

Kock, N. (2023). Contributing to the success of PLS in SEM: An action research perspective. *Communications of the Association for Information Systems*, 52(1), 730-734.

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, 28(1), 227–261.

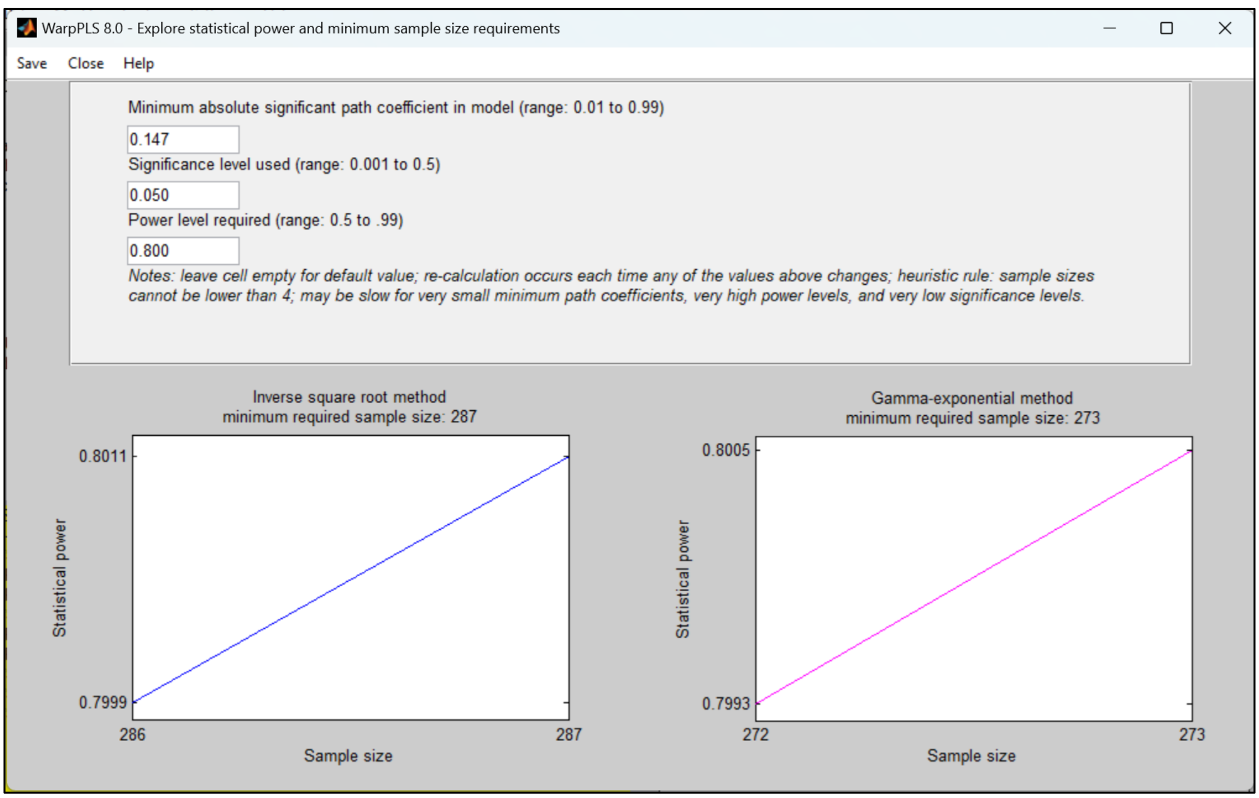
Kock, N., & Lynn, G.S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, 13(7), 546-580.

Mayfield, J., & Mayfield, M. (2017). *Motivating language theory: Effective leader talk in the workplace*. New York, NY: Springer.

Appendix A: Minimum sample size estimation in WarpPLS

Figure A.1 shows how one can use the sub-option *Explore statistical power and minimum sample size requirements*, under the *Explore* menu option in WarpPLS. The significance level was set at 0.05, the power level was set at 0.8, and the minimum expected absolute path coefficient in the model was set at 0.147. Based on these settings (the first two are standard settings in SEM), we obtained minimum required sample size estimates of 287 and 273, respectively for the inverse square root and gamma-exponential methods.

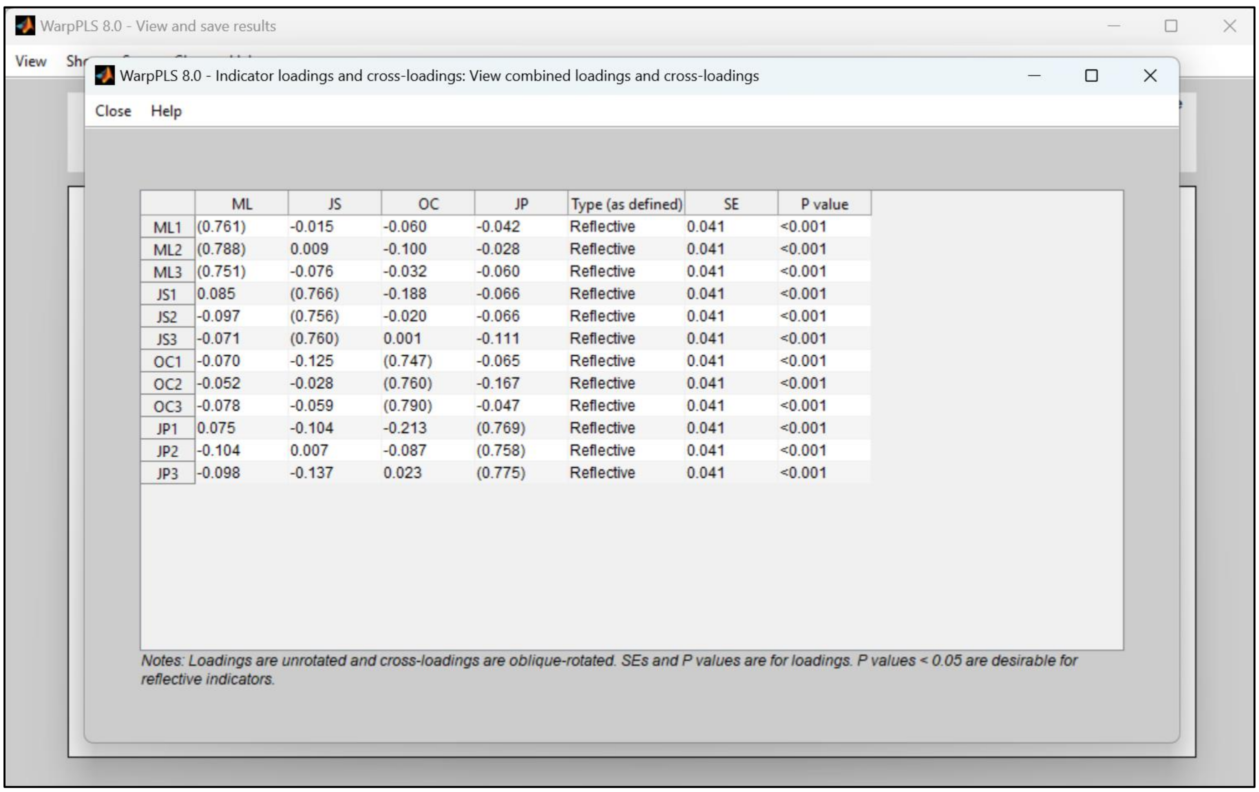
Figure A.1: Minimum sample size estimation in WarpPLS



Appendix B: Loadings and cross-loadings for LVs in WarpPLS

Figure B.1 shows how the loadings and cross-loadings for LVs would look in WarpPLS. The cells containing the loading and cross-loadings are shown under the columns indicated as ML, JS, OC and JP. We selected them and copied their contents into the clipboard. We then pasted the contents into Word as unformatted text, and inserted a table around them. This procedure makes the transfer of content from WarpPLS into Word a fairly straightforward task.

Figure B.1: Loadings and cross-loadings for LVs in WarpPLS



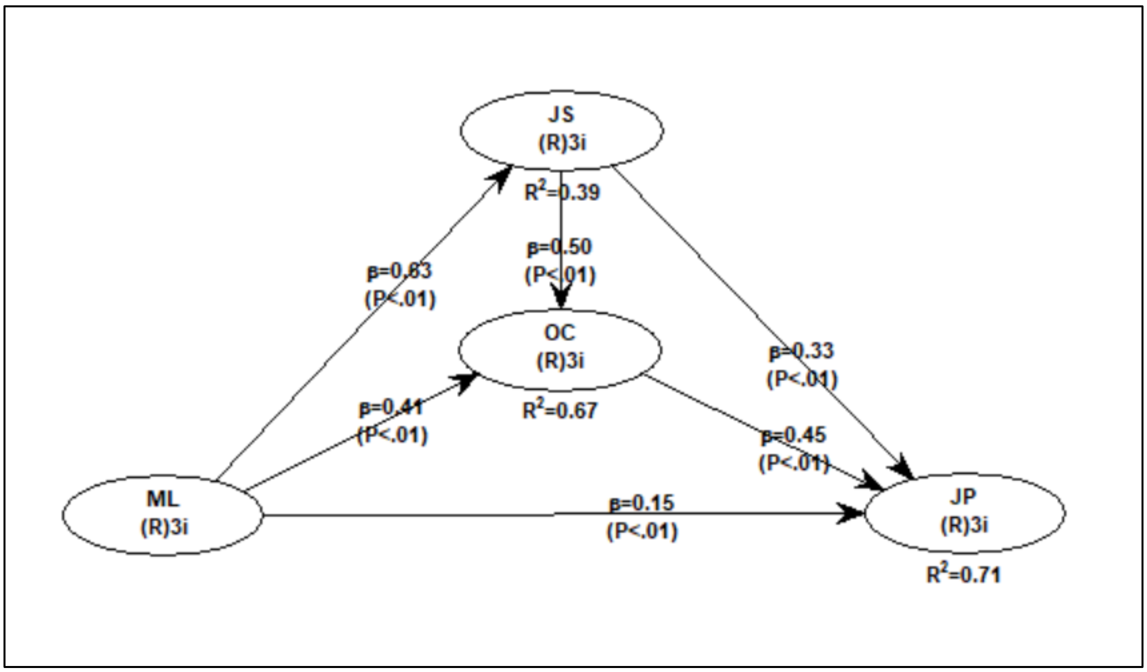
	ML	JS	OC	JP	Type (as defined)	SE	P value
ML1	(0.761)	-0.015	-0.060	-0.042	Reflective	0.041	<0.001
ML2	(0.788)	0.009	-0.100	-0.028	Reflective	0.041	<0.001
ML3	(0.751)	-0.076	-0.032	-0.060	Reflective	0.041	<0.001
JS1	0.085	(0.766)	-0.188	-0.066	Reflective	0.041	<0.001
JS2	-0.097	(0.756)	-0.020	-0.066	Reflective	0.041	<0.001
JS3	-0.071	(0.760)	0.001	-0.111	Reflective	0.041	<0.001
OC1	-0.070	-0.125	(0.747)	-0.065	Reflective	0.041	<0.001
OC2	-0.052	-0.028	(0.760)	-0.167	Reflective	0.041	<0.001
OC3	-0.078	-0.059	(0.790)	-0.047	Reflective	0.041	<0.001
JP1	0.075	-0.104	-0.213	(0.769)	Reflective	0.041	<0.001
JP2	-0.104	0.007	-0.087	(0.758)	Reflective	0.041	<0.001
JP3	-0.098	-0.137	0.023	(0.775)	Reflective	0.041	<0.001

Notes: Loadings are unrotated and cross-loadings are oblique-rotated. SEs and P values are for loadings. P values < 0.05 are desirable for reflective indicators.

Appendix C: Illustrative model in WarpPLS

Figure C.1 shows how the illustrative model would look in WarpPLS. As noted earlier, it is generally not recommended to use model screen shots taken directly from the software. One possible exception to this general rule of thumb would be methodological articles such as this, but primarily when these articles are published in tool-specific journals (e.g., the Data Analysis Perspectives Journal).

Figure C.1: Illustrative model in WarpPLS



Notes: ML = motivating language; JS = job satisfaction; OC = organizational commitment; JP = job performance; notation under LV acronym describes measurement approach and number of indicators, e.g., (R)3i = reflective measurement with 3 indicators.