The assessment of the performance of covariance-based structural equation modeling and partial least square path modeling

Conference Paper *in* AIP Conference Proceedings · May 2017

DOI: 10.1063/1.4982839

4 authors:


Ahmad Nazim Aimran
Universiti Malaysia Terengganu
18 PUBLICATIONS **95** CITATIONS


Sabri Ahmad
Universiti Malaysia Terengganu
35 PUBLICATIONS **168** CITATIONS


Asyraf Afthanorhan
Universiti Sultan Zainal Abidin | UniSZA
45 PUBLICATIONS **386** CITATIONS


Zainudin Awang
Universiti Sultan Zainal Abidin | UniSZA
83 PUBLICATIONS **403** CITATIONS

The assessment of the performance of covariance-based structural equation modeling and partial least square path modeling

Ahmad Nazim Aimran, Sabri Ahmad, Asyraf Afthanorhan, and Zainudin Awang

Citation: AIP Conference Proceedings **1842**, 030001 (2017); doi: 10.1063/1.4982839
View online: http://dx.doi.org/10.1063/1.4982839
View Table of Contents: http://aip.scitation.org/toc/apc/1842/1
Published by the American Institute of Physics

The Assessment of the Performance of Covariance-Based Structural Equation Modeling and Partial Least Square Path Modeling

Ahmad Nazim Aimran[1,a)], Sabri Ahmad[1], Asyraf Afthanorhan[2] and Zainudin Awang[2]

[1]Schools of Informatics and Applied Mathematics, Universiti Malaysia Terengganu, 21300 Kuala Terengganu, Terengganu.
[2]Faculty of Economics and Management Sciences, Universiti Sultan Zainal Abidin, 21300 Kuala Terengganu, Terengganu.

[a)]Corresponding author: ahmadnazim10@gmail.com

Abstract. Structural equation modeling (SEM) is the second generation statistical analysis technique developed for analyzing the inter-relationships among multiple variables in a model. Previous studies have shown that there seemed to be at least an implicit agreement about the factors that should drive the choice between covariance-based structural equation modeling (CB-SEM) and partial least square path modeling (PLS-PM). PLS-PM appears to be the preferred method by previous scholars because of its less stringent assumption and the need to avoid the perceived difficulties in CB-SEM. Along with this issue has been the increasing debate among researchers on the use of CB-SEM and PLS-PM in studies. The present study intends to assess the performance of CB-SEM and PLS-PM as a confirmatory study in which the findings will contribute to the body of knowledge of SEM. Maximum likelihood (ML) was chosen as the estimator for CB-SEM and was expected to be more powerful than PLS-PM. Based on the balanced experimental design, the multivariate normal data with specified population parameter and sample sizes were generated using Pro-Active Monte Carlo simulation, and the data were analyzed using AMOS for CB-SEM and SmartPLS for PLS-PM. Comparative Bias Index (CBI), construct relationship, average variance extracted (AVE), composite reliability (CR), and Fornell-Larcker criterion were used to study the consequence of each estimator. The findings conclude that CB-SEM performed notably better than PLS-PM in estimation for large sample size (100 and above), particularly in terms of estimations accuracy and consistency.

INTRODUCTION

Structural equation modeling (SEM) is a method for studying the causal relationship between multiple variables assumed to be directly or indirectly (structural model) causally associated each other and thereby including the exogenous, endogenous, interaction, and intervening constructs (Svahn & Wahlund, 2015; Afthanorhan, Aimran & Sabri, 2015). Two families of SEM have prevailed (Chin, 1998): covariance-based structural equation modeling (CB-SEM) and variance-based structural equation modeling (VB-SEM) (Dijkstra & Henseler, 2015). SEM has been heralded as a unified model that joins methods from econometrics, psychometrics, sociometrics, and multivariate statistics (Bentler, 1994), whereas VB-SEM is an alternative technique to replace the traditional SEM (Lohmöller, 1989; Hair et al., 2011; Kock, 2014). The latter involves different techniques such as regression on summed scale (Tenenhaus, 2008), generalized structured component analysis based structural equation modeling (GSCA-SEM) (Henseler, 2012; Hwang & Takane, 2004), and partial least square path modeling (PLS-PM) (Wold, 1982; Henseler, Ringle & Sinkovics, 2009). Among the VB-SEM techniques, PLS-PM has been regarded as the most fully

The 3rd ISM International Statistical Conference 2016 (ISM-III)
AIP Conf. Proc. 1842, 030001-1–030001-10; doi: 10.1063/1.4982839
Published by AIP Publishing. 978-0-7354-1512-6/$30.00

developed and it has been adopted in most studies of behavioral sciences (McDonald, 1996; Dijkstra & Henseler, 2015). The method has gained increasing interest among marketing researchers in recent years and to date, it has been recognized as a composite modeling that utilizes the weighted linear composite or factor score to determine the path relationship between exogenous and endogenous constructs (Rönkkö & Evermann, 2013; McIntosh, Edwards & Antonakis, 2014).

This study was motivated by the awareness that many researchers nowadays tend to use PLS-PM because of its less stringent assumption and the need to avoid perceived difficulties in CB-SEM (Johansson & Yip, 1994; Howell & Hall-Meranda, 1999; Bass et al., 2003; Henseler et al., 2009). The aim of the present article is to (a) compare the parameter estimates of CB-SEM and PLS-PM, (b) assess the convergent validity and construct/composite reliability of CB-SEM and PLS-PM, and (c) assess the discriminant validity in CB-SEM and PLS-PM. The purpose is to provide clarification for thought on CB-SEM and PLS-PM for researchers.

SIMULATION STUDY OF CB-SEM AND PLS-PM

We created multivariate normal data with four constructs. By taking into account that PLS is typically applied if the sample size is rather small (Dijkstra & Henseler, 2015), we chose sample sizes of 50, 100, 200, and 500 observations. Every conceptualization of four reflective measurement models was measured by four indicators, each consisting of four indicators with homogenous true indicator loading of λ = 0.60 and λ = 0.70 respectively. The choice of λ = 0.60 as true indicator loadings was induced by the parameter value, which has been frequently noted as the minimum requirement for validating the measurement model under confirmatory factor analysis. The population constructs relationships were specified to be heterogeneous (see Fig. 1). Then, the data were generated by drawing multivariate normal samples and the mean vector from the population model. The full factorial design for this study was 4 cells (N = 50, 100, 200, and 500). Each sample was estimated by using CB-SEM and PLS-PM. The simulation approach was conducted using the R statistical programming environment. For the statistical inferential, we used IBM AMOS version 21.0 for the CB-SEM analysis and SmartPLS 2.0 for the PLS-PM analysis.

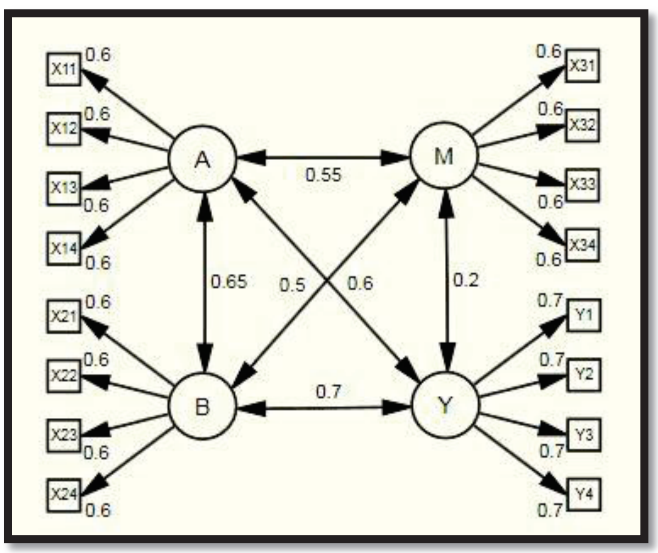

FIGURE 1. The population model

METHODOLOGY

Comparative Bias Index (CBI)

$$CBI = 1 - \frac{\left|\hat{\theta} - \theta\right|}{\theta} \qquad (1)$$

where θ is the true value of the model parameter of interest and $\hat{\theta}$ is its estimates. A CBI value of > 0.9 indicates unbiased or low bias of estimate, and a CBI value of > 0.8 indicates acceptable bias of estimate. Otherwise it is unacceptable bias estimate.

Average Variance Expected (AVE)

AVE represents the average amount of variance that a construct explains in its indicator variables relative to the overall variance of its indicators. It equates the average squared standardized loading and is equivalent to the mean value of the indicator reliabilities (Henseler, Ringle & Sarstedt, 2015). According to Fornell & Larcker (1981),

$$AVE = \frac{\sum_{i=1}^{p} \lambda_i^2}{\sum_{i=1}^{p} \lambda_i^2 + \sum_{i=1}^{p} \theta_{\delta i i}} \qquad (2)$$

where p is the number of observed indicators $(i = 1$ though $p)$, λ_i are the indicator loadings, and $\theta_{\delta i i}$ are the measurement error variances.

Composite Reliability (CR)

Composite reliability assumes a single-factor model with the variance of the factor fixed to unity. With this specification, the formula for the CR is as follows (Jöreskog, 1971):

$$CR = \frac{\left(\sum_{i=1}^{p} \lambda_i\right)^2}{\left(\sum_{i=1}^{p} \lambda_i\right)^2 + \sum_{i=1}^{p} \theta_{\delta i i}} \qquad (3)$$

where p is the number of observed indicators $(i = 1$ though $p)$, λ_i are the indicator loadings, and $\theta_{\delta i i}$ are the measurement error variances.

Discriminant Validity

According to Fornell-Larcker (1981), discriminant validity can be assessed by comparing the amount of the variance captured by the construct $(AVE\xi_j)$ and the shared variance with other constructs (ϕ_{ij}). Thus, the levels of square root of the AVE for each construct should be greater than the correlation involving the constructs:

$$\sqrt{AVE\xi_j} \geq \phi_{ij}, \quad \forall i \neq j \tag{4}$$

Otherwise, the levels of the AVE for each construct should be greater than the squared correlation involving the constructs:

$$AVE\xi_j \geq \phi_{ij}^2, \quad \forall i \neq j \tag{5}$$

FINDINGS

We explored the performance of CB-SEM and PLS-PM in the form of CBI, constructs relationship, AVE, CR, and Fornell-Larcker criterion for a model across four sample sizes. We also conducted the normality tests for all generated data. Skewness and kurtosis of the data were satisfied, indicating that the data were normally distributed.

TABLE 1. Comparison of CBI for Indicator Loading

Sample size	Item	True Loading	Loading Estimate CB-SEM	Loading Estimate PLS-PM	CBI Loading CB-SEM	CBI Loading PLS-PM
50	X11	.60	.331	.626	.552	.957
	X12	.60	.507	.696	.845	.840
	X13	.60	.155	.555	.258	.925
	X14	.60	.224	.459	.373	.765
	X21	.60	.537	.649	.895	.918
	X22	.60	.740	.811	.767	.648
	X23	.60	.727	.816	.788	.640
	X24	.60	.613	.722	.978	.797
	X31	.60	.481	.644	.802	.927
	X32	.60	.523	.608	.872	.987
	X33	.60	.554	.754	.923	.743
	X34	.60	.564	.695	.940	.842
100	X11	.60	.692	.797	.847	.672
	X12	.60	.655	.763	.908	.728
	X13	.60	.517	.661	.862	.898
	X14	.60	.542	.659	.903	.902
	X21	.60	.493	.638	.822	.937
	X22	.60	.678	.784	.870	.693
	X23	.60	.458	.612	.763	.980
	X24	.60	.689	.784	.852	.693
	X31	.60	.503	.653	.838	.912
	X32	.60	.571	.696	.952	.840
	X33	.60	.576	.710	.960	.817
	X34	.60	.631	.742	.948	.763
200	X11	.60	.619	.717	.968	.805
	X12	.60	.583	.709	.972	.818
	X13	.60	.570	.711	.950	.815
	X14	.60	.692	.775	.847	.708
	X21	.60	.627	.744	.955	.760
	X22	.60	.507	.636	.845	.940
	X23	.60	.602	.708	.997	.820
	X24	.60	.590	.741	.983	.765
	X31	.60	.648	.766	.920	.723
	X32	.60	.629	.780	.952	.700
	X33	.60	.607	.699	.988	.835
	X34	.60	.504	.608	.840	.987
500	X11	.60	.563	.698	.938	.837
	X12	.60	.525	.687	.875	.855
	X13	.60	.561	.679	.935	.868
	X14	.60	.587	.718	.978	.803
	X21	.60	.545	.690	.908	.850
	X22	.60	.541	.686	.902	.857
	X23	.60	.576	.703	.960	.828
	X24	.60	.569	.702	.948	.830

Table 1 shows the comparison of indicator loading CBI between CB-SEM and PLS-PM. The results show that when the sample size was small (n = 50), both CB-SEM and PLS-PM consisted of 3 and 5 low CBI value (< 0.8) indicator respectively. This finding indicates that at low sample size, both CB-SEM and PLS-PM generated a number of biased indicator loading estimates, but when the sample size was n = 100 and the CB-SEM consisted of only 1 low CBI value (< 0.8) indicator, the PLS-PM consisted of 5 low CBI value (< 0.8) indicators. Meanwhile, in $n \geq 200$, CB-SEM consisted of 0 low CBI value (< 0.8) indicator and PLS-PM consisted a total of 7 low CBI value (< 0.8) indicators. These findings indicate that the estimation of CB-SEM was consistent as the sample size increased, and vice-versa for PLS-PM. The result confirms that the estimation of indicator loading in CB-SEM was better than that in PLS-PM when the sample size was large ($n \geq 100$). The biasness of indicator loading estimates in PLS-PM might be due to its overestimation. A closer look at the indicator loading estimates revealed that PLS-PM tended to produce higher estimation compared to CB-SEM and exhibit notable difference from the true loading. Consequently, the overestimation of indicator loading estimates would have led to the overestimation of AVE and CR. Considering that all items remained in the model, the AVE and CR estimations obtained are as follows:

TABLE 2. Comparison of AVE and CR

Sample size	Construct	AVE		CR	
		CB-SEM	**PLS-PM**	**CB-SEM**	**PLS-PM**
50	A	.110	.349	.294	.677
	B	.435	.566	.752	.838
	M	.282	.459	.611	.771
	Y	.426	.563	.747	.837
100	A	.367	.522	.696	.813
	B	.347	.502	.673	.800
	M	.327	.492	.659	.794
	Y	.489	.613	.793	.864
200	A	.382	.531	.711	.819
	B	.340	.502	.672	.801
	M	.360	.513	.690	.807
	Y	.499	.624	.799	.869
500	A	.313	.484	.645	.790
	B	.311	.483	.644	.789
	M	.340	.503	.672	.801
	Y	.450	.587	.766	.850

Table 2 shows the comparison of AVE and CR values of CB-SEM and PLS-PM across four sample sizes (n = 50, 100, 200, and 500 respectively). As featured, while the AVE for all constructs in all sample sizes in CB-SEM were lower than 0.5, the PLS-PM only detected a total of 5 constructs having AVE values of less than 0.5. Not much difference was noted in the CR values between CB-SEM and PLS-PM in detecting low CR value (< 0.6) where the difference is only one. Rigorous observation revealed that when estimated by PLS-PM, the AVE and CR values of constructs tended to be higher than CB-SEM. An AVE < 0.5 and a CR < 0.6 indicate that the convergent validity and composite reliability were not achieved. The consequence of overestimation of indicator loading led to the PLS-PM becoming less sensitive in detecting convergent validity and composite reliability. The overestimation of AVE would have led to the overestimation of $\sqrt{AVE}$ and may have affected the sensitivity in detecting discriminant validity. Table 3 compares the Fornell-Larcker criterion.

TABLE 3. Comparison of Fornell-Larcker Discriminant Validity

	Sample size	Construct	A	B	M	Y
CB-SEM	50	A	.332			
		B	.845	.660		
		M	.512	.329	.531	
		Y	.974	.721	.224	.653
	100	A	.606			
		B	.685	.589		
		M	.556	.469	.572	
		Y	.585	.614	.187	.699
	200	A	.618			
		B	.649	.583		
		M	.602	.423	.600	
		Y	.655	.651	.264	.706
	500	A	.559			
		B	.733	.558		
		M	.518	.501	.583	
		Y	.624	.723	.233	.671
	Sample size	**Construct**	**A**	**B**	**M**	**Y**
PLS-PM	50	A	.591			
		B	.403	.752		
		M	.530	.234	.677	
		Y	.483	.575	.183	.750
	100	A	.722			
		B	.484	.709		
		M	.382	.335	.701	
		Y	.459	.464	.076	.783
	200	A	.729			
		B	.454	.709		
		M	.430	.305	.716	
		Y	.516	.478	.275	.790
	500	A	.696			
		B	.469	.695		
		M	.346	.334	.709	
		Y	.442	.510	.172	.766

It can be clearly observed in Table 3 that most of the $\sqrt{AVE}$ in CB-SEM are lower than its respective row and column correlation between construct values, which caused the discriminant validity to not be achieved in all the sample sizes. However, the results obtained in PLS-PM were notably different in which discriminant validity was achieved across all sample sizes. Thorough observation showed that the between-construct correlation of PLS-PM was much lower than the true population correlation. The overestimation of $\sqrt{AVE}$ values and the underestimation of between-constructs correlation in PLS-PM caused no discriminant validity concern to be observed in PLS-PM. Diligent observation revealed that all between-construct correlation estimates by PLS-PM were lower than those by CB-SEM.

TABLE 4. Comparison of CBI for Correlation between Constructs

Sample size	Corr	True Corr	Corr (CB-SEM)	Corr (PLS-PM)	CBI Corr (CB-SEM)	CBI Corr (PLS-PM)
50	A, B	.65	.845	.403	.700	.620
	A, M	.55	.512	.530	.931	.964
	A, Y	.60	.974	.483	.377	.805
	B, M	.50	.329	.234	.658	.468
	B, Y	.70	.721	.575	.970	.821
	M, Y	.20	.224	.127	.880	.635
100	A, B	.65	.685	.484	.946	.745
	A, M	.55	.556	.382	.989	.695
	A, Y	.60	.585	.459	.975	.765
	B, M	.50	.469	.335	.938	.670
	B, Y	.70	.614	.464	.877	.663
	M, Y	.20	.187	.076	.935	.380
200	A, B	.65	.649	.454	.998	.698
	A, M	.55	.602	.430	.905	.782
	A, Y	.60	.655	.516	.908	.860
	B, M	.50	.423	.305	.846	.610
	B, Y	.70	.651	.478	.930	.683
	M, Y	.20	.264	.275	.680	.625
500	A, B	.65	.733	.469	.872	.722
	A, M	.55	.518	.346	.942	.629
	A, Y	.60	.624	.442	.960	.737
	B, M	.50	.501	.334	.998	.668
	B, Y	.70	.723	.510	.967	.729
	M, Y	.20	.233	.172	.835	.860

Note: Corr refers to correlation between constructs

Table 4 shows the comparison of constructs' correlation CBI between CB-SEM and PLS-PM. Similarly, when the sample size was small (n=50), both CB-SEM and PLS-PM consisted of 3 low CBI value (< 0.8) correlation respectively. This finding indicates that for low sample size, both CB-SEM and PLS-PM generated a number of biased correlation estimates but when the sample size was $n \geq 100$ and the CB-SEM consisted of only 1 low CBI value (< 0.8) correlation, the PLS-PM consisted of 16 low CBI values (< 0.8) correlation. This finding indicates that as the sample size increases, the accuracy and consistency of correlation between constructs in CB-SEM increases, but not in PLS-PM. By relating the findings in Table 3 and Table 4, it is clearly observed that the correlation between constructs in PLS-PM has been underestimated.

CONCLUSION AND DISCUSSION

Previous studies have argued on the use of PLS-PM and its capabilities in statistical analysis. By using a simulation study, we generated data using a simple model under conservative conditions (e.g., normal, complete data) with various sample sizes. The data were then analyzed by using CB-SEM and PLS-PM to investigate their respective performance. We have attested the claims in previous studies on the performance of CB-SEM and PLS-PM by displaying the results obtained.

A thorough observation on the estimated values of CB-SEM and PLS-PM revealed that in all sample sizes, PLS-PM generated higher indicator loading estimates compared to CB-SEM. This finding explains Rönkkö & Evermann's (2013) claims which state that composite (indicator) loading in PLS will always be higher than factor loading in CB-SEM because composite loading also explains part of the error variance. Resulting from this, the tendency of PLS-PM in detecting low reliability items (< 0.6) is low. Accordingly, the researchers are interested in examining latent constructs and are recommending the use of CB-SEM which is more sensitive in detecting low reliability indicators. Consequently, the overestimation of indicator loading in PLS-PM will affect CR and AVE values.

Also notable was the consequence of overestimation of indicator loading, and the performance of PLS-PM in detecting discriminant validity is considerably behind the CB-SEM approach. As $AVE\xi_j = \left(\sum_{k=1}^{K_j} \lambda_{jk}^2\right) \Big/ K_j$ and $CR\xi_j = \left(\sum_{k=1}^{K_j} \lambda_{jk}\right)^2 \Big/ \left[\left(\sum_{k=1}^{K_j} \lambda_{jk}\right)^2 + \left(\sum_{k=1}^{K_j} 1 - \left(\sum_{k=1}^{K_j} \lambda_{jk}^2\right)\right)\right]$ where λ_{jk} is the indicator loading, K_j is the number of indicator for construct ξ_j, the AVE and CR in PLS-PM, therefore, will always be higher than in CB-SEM. Thus, compared to CB-SEM, the tendency of PLS-PM to detect if convergent validity is not achieved (i.e., AVE < 0.5) is low. In connection with this, the model discriminant validity will be affected as well.

It is well known that VB-SEM methods tend to overestimate indicator loadings (e.g., Lohmöller, 1989). The origin of this characteristic lies in the methods' treatment of constructs. VB-SEM methods, such as PLS or GSCA, use composites of indicator variables as substitutes for the underlying constructs (Henseler et al., 2014). The loading of each indicator on the composite represents a relationship between the indicator and the composite of which the indicator is part. As a result, the degree of overlap between each indicator and composite will be high, yielding inflated loading estimates, especially if the number of indicators per construct (composite) is small (Aguirre-Urreta et al., 2013). The VB-SEM methods generally underestimate structural model relationships (e.g., Reinartz et al., 2009) and technically, discriminant validity requires that "a test not correlate too highly with measures from which it is supposed to differ" (Campbell, 1960). Additionally, the Fornell-Larcker criterion indicates that discriminant validity is established if the following condition $\sqrt{AVE\xi_j} > \max r_{ij}$ holds where $AVE\xi_j$ is the AVE value at construct ξ_j and r_{ij} be the correlation coefficient between the construct scores of constructs ξ_i and ξ_j. Referring to this and supported with the result obtained, we therefore conclude that PLS-PM is less sensitive in detecting discriminant validity if the Fornell-Larcker criterion is used. We therefore suggest the use of heterotrait-monotrait ratio of correlation (HTMT) as proposed by Henseler et al. (2015) if researchers insist on using PLS-PM. Further, we would like to note that all conclusions made in this study may only be inferred to the model within the scope of this study. We do not deny that PLS-PM may be a good estimator if the true indicator loadings are reliably high (e.g., ≥ 0.8). We therefore conclude that in the case where the true indicator loadings are in the range of 0.6 to 0.7 and where the true correlations between constructs are heterogeneous as in this study, CB-SEM Maximum Likelihood is a better choice of estimation to be used by researchers.

ACKNOWLEDGMENTS

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication. The author(s) received no financial support for the research, authorship, and/or publication of this article.

REFERENCES

1. A. Afthanorhan, A. N. Aimran and A. Sabri, Parametric Approach Using Z-Test for Comparing 2 Means to Multi-Group Analysis in Partial Least Square Structural Equation Modeling (PLS-SEM), British Journal of Applied Science & Technology **6**(2), 194 (2015).
2. M. I. Aguirre-Urreta, G. M. Marakas and M. E. Ellis, Measurement of Composite Reliability in Research Using Partial Least Squares: Some Issues And An Alternative Approach, SIGMIS Database **44**(4), 11-43 (2013).
3. B. M. Bass, B. J. Avolio, D. I. Jung and Y. Berson, Predicting Unit Performance by Assessing Transformational and Transactional Leadership, Journal of Applied Psychology **88**(2), 207-218 (2003).
4. D. T. Campbell, Recommendations for APA Test Standards Regarding Construct, Trait, or Discriminant Validity, American Psychologist **15**(8), 546-553 (1960).
5. W. W. Chin, "The Partial Least Squares Approach to Structural Equation Modeling," in *Modern Methods for Business Research*, edited by G. A. Marcoulides (Mahwah, NJ, USA: Erlbaum; 1998), pp. 295–336.
6. T. K. Dijkstra and J. Henseler, Consistent and Asymptotically Normal PLS Estimators for Linear Structural Equations, Computational Statistics & Data Analysis **81**, 10-23 (2015).
7. C. Fornell and D. F. Larker, Evaluating Structural Equation Models with Unobservable Variables and Measurement Error, Journal of Marketing Research, 39-50 (1981).
8. J. F. Hair, C. M. Ringle and M. Sarstedt, PLS-SEM: Indeed a Silver Bullet, Journal of Marketing Theory & Practice **19**(2), 139-152 (2011).
9. J. Henseler, T. K. Dijkstra, M. Sarstedt and C. M. Ringle, A. Diamantopoulos, D. Straub, R. Calantone, Common Beliefs and Reality about PLS, Organizational Research Methods **17**(2), 182-209 (2014).
10. J. Henseler, Why Generalized Structured Component Analysis Is Not Universally Preferable to Structural Equation Modeling, Journal of the Academy of Marketing Science **40**(3), 402-413 (2012).
11. J. Henseler, C. M. Ringle and M. Sarstedt, A New Criterion For Assessing Discriminant Validity In Variance-Based Structural Equation Modelling, Journal of The Academy and Marketing Science **43**, 115-135 (2015).
12. J. Henseler, C. M. Ringle and R. R. Sinkovics, The Use of Partial Least Squares Path Modeling in International Marketing, Advances in International Marketing (AIM) **20**, 277-320 (2009).
13. J. M. Howell and K. E. Hall-Merenda, The Ties That Bind: The Impact of Leader-Member Exchange, Transformational and Transactional Leadership, and Distance on Predicting Follower Performance, Journal of Applied Psychology **84**(5), 680-694 (1999).
14. H. Hwang and Y. Takane, Generalized Structured Component Analysis, Psychometrika **69**(1), 81-99 (2004).
15. J. K. Johansson and G. S. Yip, Exploiting Globalization Potential: U.S. and Japanese Strategies, Strategic Management Journal **15**(8), 579-601 (1994).
16. K. G. Jöreskog, Statistical Analysis off Sets of Congeneric Tests, Psychometrika **36**, 109-133 (1971).
17. N. Kock, Advanced Mediating Effects Tests, Multi-Group Analyses, and Measurement Model Assessments in PLS-Based SEM, International Journal of e-Collaboration (IJeC) **10**(1), 1-13 (2014).
18. J. B. Lohmöller, *Latent Variable Path Modeling with Partial Least Squares* (Physica-Verlag, Heidelberg, Germany, 1989).
19. R. P. McDonald, Path Analysis with Composite Variables, Multivariate Behavioral Research **31**(2), 239-270 (1996).
20. C. N. McIntosh, J. R. Edwards and J. Antonakis, Reflections on Partial Least Squares Path Modeling, Organizational Research Methods **17**(2), 210-251 (2014).

21. W. Reinartz, M. Haenlein and J. Henseler, *An Empirical Comparison of the Efficacy of Covariance-Based and Variance-Based SEM* (INSEAD, Fontainebleau, France, 2009) pp. 1-51.
22. M. Rönkkö and J. Evermann, A Critical Examination of Common Beliefs about Partial Least Squares Path Modeling, Organizational Research Methods **16**(3), 425-448 (2013).
23. M. Svahn and R. Wahlund, "Structural Equation Modelling for Studying Intended Game Processes" in *Game Research Methods,* ETC Proceeding, edited by L. Bjork et al. (Library of Congress Control, 2015), pp. 251-267.
24. M. Tenenhaus, Component-Based Structural Equation Modelling, Total Quality Management **19**(7-8), 871-886 (2008).
25. H. Wold, "Soft Modelling: The Basic Design and Some Extensions" in *Systems Under Indirect Observation: Causality, Structure, Prediction,* edited by K. G. Jöreskog and H. Wold (Business and Economics, North-Holland, 1982), pp. 1-54.