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A comparative study on the performance of maximum likelihood, generalized least square, scale-free least square, partial least square and consistent partial least square estimators in structural equation modeling

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A B S T R A C T

Structural equation modeling offers various estimation methods for estimating parameters. The most used method in covariance-based structural equation modeling (CB-SEM) is the maximum likelihood (ML) estimator. The ML estimator is typically used when fitting models with normally distributed data. The growth of partial least squares path modeling (PLS-PM), including consistent partial least squares (PLSc), has also been noticed by researchers in the SEM fields. The PLSc has elevated interest in the scholastic setting in measuring the performance of various estimation methods in structural equation modeling. The choice of estimation methods has substantial impact in yielding parameter estimates. There could be a trade-off among the estimation methods' ability to deal with different types of data based on the model tested. Accordingly, this study aims to compare the performance of ML, generalized least squares (GLS), and scale-free least squares (SFLS) for CB-SEM as well as partial least squares (PLS) and consistent partial least squares (PLSc). Multivariate normal data were generated using Monte Carlo simulation with pre-determined population parameters and sample sizes using R Programming packages. To produce the estimated values, data analysis was performed using AMOS and SmartPLS for CB-SEM and PLS-SEM, respectively. The findings illustrate notable similarities between CB-SEM (ML) and PLS-SEM results when the true indicator loading is certainly high.

1. Introduction

The second-generation statistical analysis technique, structural equation modeling (SEM), is established for evaluating the inter-relationships among numerous variables in a model (Awang, 2015; Ainur et al., 2017). The covariance-based SEM (CB-SEM) and variance-based SEM (VB-SEM) are the two most widely used methods in SEM (Henseler et al., 2016). PLS-SEM is presently the most fully developed of the VB-SEM approaches, commonly employed for fitting and testing hypotheses (McDonald, 1996; Schamberger et al., 2020). PLS-SEM has also been widely used in most social science fields (Hair et al., 2018). While CB-SEM is generally developed for confirmatory research, VB-SEM is known as a prediction-based approach to SEM that is mostly utilized for exploratory research (Sarstedt et al., 2014). The goal of CB-SEM is to estimate model parameters that minimize the discrepancies between the observed sample covariance matrix once the improved theoretical model has been validated (Awang, 2015). The normality of data distributions is necessary for several estimators in CB-SEM, which is rarely encountered in social sciences study. PLS-SEM, on the other hand, not only functions well with non-normal

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data but also has very few limitations when it comes to the application of ordinal and binary scales (Hair et al., 2017).

Apart from ML, several other estimators in CB-SEM have been developed to deal with different data characteristics, such as generalized least squares (GLS) and scale-free least squares SFLS (Hair. et al., 2017; Takane & Hwang, 2018). Despite performing less well, the GLS fit function is able to minimize the disparities between a sample covariance matrix and the covariance matrix of a theoretical model like ML. Meanwhile, the SFLS fit function, which is derived from the GLS, is rarely used in past studies. Despite the widespread use of SEM in various fields, little has been researched on its estimation techniques (Andreassen et al., 2006). Thus, we think it is important to study the accuracy of estimation methods when fitting SEM models of different data characteristics. The development of PLSc by Dijkstra in 2010 was claimed to have resolved many SEM issues. The method is said to mimic the ML estimator in CB-SEM (Dijkstra & Henseler, 2015) since it applies an attenuation adjustment to estimate factor loadings and path coefficients consistently (Schamberger et al., 2020). Therefore, we intend to examine whether PLSc performs better than the conventional PLS-PM and CB-SEM methods in measuring the parameter estimates. Towards this end, we used the comparative bias index (CBI) developed by Aimran et al. (2017b) and compared the indicator loadings estimations between ML, GLS, SFLS, PLS, and PLSc.

2. Methodology

2.1 Research model for simulation

In this study, we used the Monte Carlo Markov Chain (MCMC) simulation procedures to generate normally distributed data. We created three population models with different specifications of true indicator loadings. Each model had four latent constructs consisting of homogenous true indicator loading of 0.7, 0.8, and 0.9 and correlation of 0.7, respectively. High indicator loading was set to avoid underestimation when using small sample sizes. Relationships between the constructs of the population were characterized as homogeneous. Sample sizes of 50, 100, 200, and 500 were opted, since PLS is commonly employed for small sample size (Dijkstra & Henseler, 2015) and that a starting point of 100 to 200 is normally used as a sample size in path modeling (Awang, 2015). CB-SEM and PLS-SEM were employed to estimate the indicator loading using IBM AMOS version 24.0 and SmartPLS 3.0 respectively. Meanwhile, the R statistical programming environment was used to conduct the simulation procedure. The "psych" package, "MASS" package, "foreign" package, and the "semTools" package were used to generate multivariate normal data. Fig. 1, Fig. 2, and Fig. 3 present the population models that were tested with several estimation methods in CB-SEM and PLS-SEM.

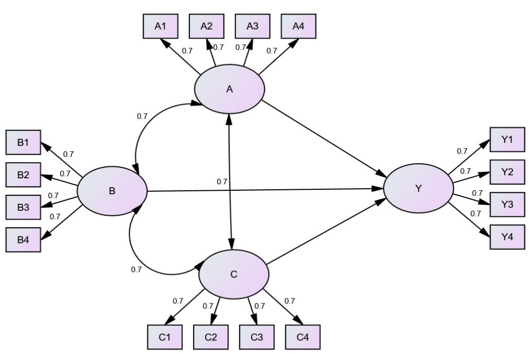

Fig. 1. Model 1

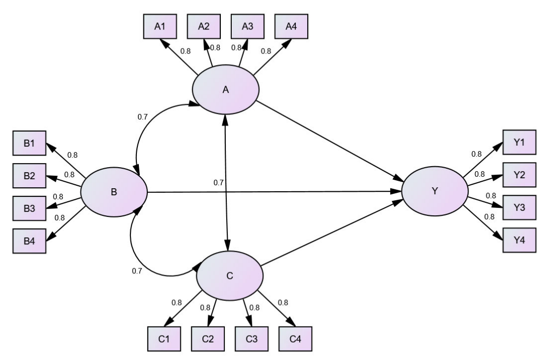

Fig. 2. Model 2

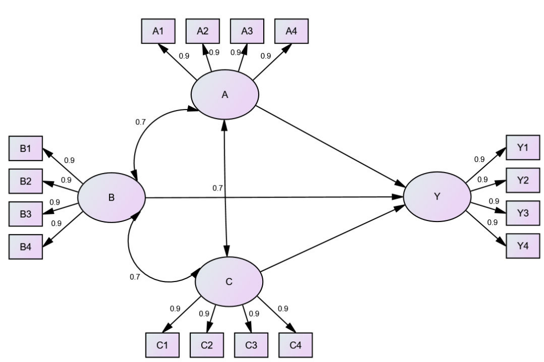

Fig. 3. Model 3

2.2 Estimation Methods

a. Maximum Likelihood (ML)

For predicting fit and coefficients in CB-SEM, the Maximum Likelihood (ML) estimation approach is often used. ML utilizes derivatives to minimize the following fit function:

$$F_{ML} = \log|\Sigma\,(\theta)| + tr\left(S\Sigma^{-1}(\theta)\right) - \log|S| - (p+q) \tag{1}$$

where the covariance matrix of the theoretical model denoted as Σ, and the sample covariance matrix defined as *S*. For a square matrix B, |B| implies the determinant of B; tr(B) defines the sum of the diagonal elements of B; and $(p+q)$ is the total numbers of manifest variables indicators. The derivation of fitting function of ML assumes that the observed variables are distributed normally (Newsom, 2018).

b. Generalized Least Squares (GLS)

According to Newsom (2018), generalized least squares is an additional fitting function. It reduces the disparity between sample covariance matrix, *S* and covariance matrix, Σ. However, the GLS fit function uses a weight matrix for the residuals, defined as *W*. The fitting function is

$$F_{GLS} = \left(\frac{1}{2}\right) tr\ (\{[S - \Sigma(\theta)W^{-1}]\}^2) \tag{2}$$

The simplicity of the function indicates that other weight matrixes could be applied to correct for the violations of distributional assumptions.

c. Scale-free Least Squares (SFLS)

The scale-free least squares estimation (SFLS) fitting function is

$$F_{SFLS} = \left(\frac{1}{2}\right) tr\ (\{[D - \Sigma(\theta)W^{-1}]\}^2) \tag{3}$$

where D is the diagonal of sample covariance; *S,* the covariance matrix of the theoretical model, is denoted as Σ; and the weight matrix for the residuals is defined as *W* (Arbuckle, 2011).

d. Partial Least Squares (PLS)

The PLS algorithm, according to Henseler et al. (2009), is a series of weight vectors regressions.

The iterative estimation of latent variable scores process is repeated until the maximum number of iterations has been reached. This step includes the following procedure:

By applying the factor weighting scheme inner weights were obtained:

$$V_{ji} = \begin{cases} cov\left(Y_j; Y_i\right)\ if\ Y_j\ and\ Y_i\ are\ adjacent \\ \qquad 0\ otherwise \end{cases} \tag{4}$$

where Y_j is the latent variable (the dependent variable) and Y_i is the latent variable (the independent variable) in the structural model.

Inside approximation:

$$\tilde{Y}_j := \sum\nolimits_i b_{ji} Y_i \tag{5}$$

where $\tilde{Y}_j$ is the computation for all constructs by utilizing the weighted sum of its adjacent constructs scores, Y_i; and b_{ji} refers to the inner weights.

Outer weights; solve for Mode A block (reflective):

$$\tilde{Y}_{jn} = \sum_{kj} \tilde{W}_{kj} X_{kjn} + d_{jn} \tag{6}$$

Outer weights; solve for Mode B block (formative):

$$X_{kjn} = \tilde{W}_{kj} \tilde{Y}_{jn} + e_{kjn} \tag{7}$$

Outside approximation:

$$Y_{jn} := \sum_{kj} \tilde{W}_{kj} X_{kjn} \tag{8}$$

where X_{kjn} denotes the raw data for item k (k = 1,..., K) of construct j (j = 1,...,J); and observations n (n = 1,...,N), $\tilde{Y}_{jn}$ is the construct scores from the inside; $\tilde{W}_{kj}$ is the outer weights; d_{jn} is the error term from a bivariate regression; and e_{kjn} is the error term from a multiple regression. Under this , the updated weights (i.e., $\tilde{W}_{kj}$) and the items (i.e., X_{kjn}) are linearly combined to renew the constructs scores (i.e., Y_{jn}).

e. Consistent Partial Least Squares (PLSc)

Dijkstra and Henseler (2015) developed consistent PLS (PLSc) to ensure that the PLS-SEM is adaptable while dealing with complicated models and distributional assumptions. In the correlation between two latent variables, the purpose is to correct for measurement error. To produce the deattenuated (i.e., consistent) correlation, PLSc refines the initial estimate.

$$r_{ij}^{*} = cor(\tilde{\xi}_{\iota}, \tilde{\xi}_{J}) \tag{9}$$

where ξ is the latent variable scores. The new reliability coefficient must be utilized to assess the reliability of the construct scores, ρ_A, for each reflective construct, as presented in the following equation:

$$\rho_A = (\hat{w}'\hat{w})^2 . \frac{\hat{w}' \, (S - diag\ (S))\hat{w}}{\hat{w}'(\hat{w}\hat{w}' - diag\ (\hat{w}\hat{w}'))\hat{w}} \tag{10}$$

where $\hat{w}$ denotes the outer weights estimates and S is the sample covariance matrix. The correlation for attenuation is also needed if one of the constructs, $\tilde{\xi}_{\iota}$ or $\tilde{\xi}_{\iota}$, is formative. If both latent variables are formative, no modification is required.

$$r_{ij} = \frac{r_{ij}^{*}}{\sqrt{\rho_A\left(\tilde{\xi}_{\iota}\right) . \rho_A\left(\tilde{\xi}_{J}\right)}} \tag{11}$$

For standardized coefficients based on correlations, the conventional OLS equation is expressed as follows:

$$\beta = R_X^{-1} \, r_{Xy} \tag{12}$$

A vector of path coefficients denotes β; R_X is the correlation matrix of the indepedent variables of the structural equation; and the vector of correlations between the dependent variable and the independent variables denotes r_{Xy}.

2.3 Comparative Bias Index (CBI)

As previously mentioned, the population data was generated based on prespecified parameters and different sample sizes. The population value was identified to be the actual model parameter (e.g., true indicator loading) values, which are required to create the simulation data. Hence, the CBI values for each item in the model were compared using the CBI described to evaluate the bias of simulation data parameter estimates as follows:

$$CBI = 1 - \frac{\left|\hat{\theta} - \theta\right|}{\theta} \tag{13}$$

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

3. Result

Table 1 to 3 summarize the performance of CB-SEM's and PLS-SEM's CBI values for all indicator loadings across the three prespecified models.

Table 1
The Comparative Bias Index (CBI) - Model 1

Sample size	Items	Comparative Bias Index CB-SEM			Comparative Bias Index PLS-SEM	
		ML	GLS	SFLS	PLS	PLSc
50	A1	.886	.971	.814	.963	**.637**
	A2	.986	**.729**	.957	.836	.903
	A3	1.000	.986	.843	.927	**.681**
	A4	.914	.943	**.757**	.824	**.626**
	B1	**.771**	.943	**.757**	.857	**.600**
	B2	.914	**.429**	.986	.977	.923
	B3	.814	.843	.800	.990	**.744**
	B4	.929	.857	.900	.983	.939
	C1	.943	**.057**	.986	.931	.959
	C2	**.757**	**-.257**	.800	.917	**.780**
	C3	.843	**-.729**	**.714**	.893	**.553**
	C4	.886	**-.029**	.843	.810	**.796**
	Y1	**.543**	**.371**	**.586**	.841	**.534**
	Y2	**.543**	**.114**	**.529**	**.741**	**.559**
	Y3	.829	**.571**	.871	.907	.851
	Y4	.829	.800	.843	.801	.810
100	A1	**.743**	**.786**	**.686**	.934	**.573**
	A2	.943	.971	.971	.829	.947
	A3	.914	.900	.986	.869	.967
	A4	.814	.800	**.757**	**.786**	**.687**
	B1	.871	.900	.871	.909	.859
	B2	.914	.986	.943	.954	.949
	B3	.971	.900	1.000	.856	.983
	B4	.971	.971	.971	.947	.990
	C1	.843	.857	.843	.983	.843
	C2	.986	.929	.957	.916	.946
	C3	.900	.971	**.786**	.870	**.671**
	C4	.886	.986	.943	.976	.981
	Y1	.843	.900	.843	.984	.837
	Y2	.857	.857	.857	.979	.867
	Y3	.986	.986	.986	.859	.977
	Y4	.900	.929	.929	.946	.931
200	A1	.900	.886	.871	.929	.831
	A2	.986	.986	.986	.869	.980
	A3	.986	1.000	1.000	.896	.997
	A4	.971	.929	.957	.864	.926
	B1	.914	.929	.943	.906	.950
	B2	.900	.943	.886	.971	.880
	B3	.986	.971	.971	.859	.943
	B4	.871	.886	.900	.983	.920
	C1	.943	.971	.943	.934	.953
	C2	.986	.929	.971	.873	.954
	C3	.843	.929	**.771**	.921	**.699**
	C4	.986	.986	.986	.916	.953
	Y1	.971	.986	.971	.920	.994
	Y2	.957	1.000	.914	.904	.890
	Y3	.943	.929	.914	.847	.897
	Y4	.957	.957	.929	.906	.901
500	A1	.929	.943	.914	.920	.890
	A2	1.000	1.000	.986	.880	.983
	A3	.986	.986	.986	.883	.989
	A4	.943	.943	.929	.843	.923
	B1	.914	.929	.914	.933	.913
	B2	.957	.957	.943	.911	.927
	B3	1.000	1.000	1.000	.880	.994
	B4	.943	.957	.957	.911	.977
	C1	.943	.971	.929	.916	.923
	C2	.971	.957	.957	.876	.956
	C3	.943	.957	.914	.894	.901
	C4	.929	.929	.943	.937	.957
	Y1	.971	.971	.971	.903	.979
	Y2	.971	1.000	.971	.891	.970
	Y3	.986	.986	1.000	.889	.980
	Y4	1.000	.986	.986	.869	.966

Note: Values in bold indicate unacceptable bias estimate

Table 2
The Comparative Bias Index (CBI) - Model 2

Sample size	Items	Comparative Bias Index CB-SEM			Comparative Bias Index PLS-SEM	
		ML	GLS	SLS	PLS	PLSc
50	A1	.950	.963	.900	.964	.893
	A2	1.000	.975	.925	.918	.890
	A3	.950	.813	.925	.913	.880
	A4	1.000	.988	.913	.928	.913
	B1	.988	.925	.988	.935	.973
	B2	.913	**.750**	.913	.995	.904
	B3	.938	.850	.900	.904	.880
	B4	.963	**.763**	.938	.945	.930
	C1	.938	.838	.900	.909	.875
	C2	.863	.938	.913	.990	.936
	C3	.975	.975	.913	.955	.865
	C4	.963	.988	.988	.900	.998
	Y1	**.763**	**.788**	**.750**	.874	**.744**
	Y2	.988	.800	.975	.931	.958
	Y3	.950	.988	.975	.888	.928
	Y4	.938	**.750**	.963	.983	.913
100	A1	.925	.938	.925	.978	.924
	A2	.975	1.000	.950	.943	.923
	A3	.963	.963	.963	.963	.971
	A4	1.000	.988	.975	.945	.965
	B1	1.000	.975	.988	.931	.966
	B2	.938	.950	.950	.980	.953
	B3	.988	.988	.975	.935	.960
	B4	.875	.863	.863	.993	.861
	C1	.988	.938	.913	.935	.873
	C2	.975	.988	.963	.953	.956
	C3	.975	.963	.963	.915	.934
	C4	.950	.913	.975	.894	.984
	Y1	.863	.975	.888	.971	.889
	Y2	.975	.963	.988	.913	.990
	Y3	1.000	.988	.975	.928	.959
	Y4	.975	.950	.988	.964	.999
200	A1	.975	.988	.988	.941	.983
	A2	.963	.988	.938	.955	.921
	A3	.975	1.000	.963	.954	.955
	A4	.988	1.000	.988	.938	.981
	B1	.975	.975	1.000	.916	.993
	B2	.975	.988	.988	.956	.999
	B3	.950	.950	.950	.970	.960
	B4	.938	.925	.925	.971	.926
	C1	.988	.988	1.000	.940	.989
	C2	.963	.988	.963	.963	.975
	C3	.975	.988	.950	.946	.939
	C4	1.000	.988	1.000	.934	.998
	Y1	.938	.988	.925	.970	.914
	Y2	.988	.975	.975	.925	.970
	Y3	.963	.975	.950	.951	.948
	Y4	.963	.963	.975	.964	.990
500	A1	.938	.950	.925	.965	.921
	A2	.950	.950	.938	.973	.940
	A3	.950	.950	.950	.966	.958
	A4	.975	.975	1.000	.949	.998
	B1	.950	.938	.925	.966	.913
	B2	.938	.938	.950	.984	.955
	B3	.938	.938	.938	.973	.929
	B4	.963	.975	.963	.965	.970
	C1	.950	.963	.950	.965	.954
	C2	.888	.900	.900	.994	.905
	C3	.975	.975	.950	.953	.931
	C4	.925	.938	.938	.985	.948
	Y1	.963	.988	.975	.956	.979
	Y2	.963	.975	.950	.956	.936
	Y3	.963	.963	.925	.960	.908
	Y4	.950	.975	1.000	.964	.983

Note: Values in bold indicate unacceptable bias estimate

Table 3
The Comparative Bias Index (CBI) - Model 3

Sample size	Items	Comparative Bias Index PLS-SEM			Comparative Bias Index PLS-SEM	
		ML	GLS	SLS	PLS	PLSc
50	A1	.956	.989	.967	.921	**.793**
	A2	.922	.911	.922	.962	**.791**
	A3	.956	.956	.944	.967	.996
	A4	.978	.956	.978	.953	.967
	B1	.844	.922	**.789**	.947	.864
	B2	.867	.844	.856	.893	.803
	B3	.878	.900	.956	.974	.996
	B4	.967	.989	.967	.938	.827
	C1	.911	.878	.889	.970	1.000
	C2	.911	.922	.889	.880	.832
	C3	.967	.811	.978	.929	**.769**
	C4	.933	.811	.911	.978	.891
	Y1	.878	.944	.833	**.777**	**.661**
	Y2	.956	.811	.956	.950	.851
	Y3	.933	.900	.856	.989	.824
	Y4	.822	**.778**	.933	.904	.967
100	A1	.911	.933	.956	.979	.972
	A2	.867	.889	.833	.931	.809
	A3	.978	.978	.978	.996	.984
	A4	.956	.978	.944	.994	.947
	B1	.856	.878	.833	.933	.812
	B2	**.789**	**.789**	**.778**	.859	**.796**
	B3	.878	.878	.900	.958	.908
	B4	.989	1.000	1.000	.993	.994
	C1	.922	.967	.922	.977	.917
	C2	.889	.967	.867	.931	.857
	C3	.900	.911	.911	.957	.911
	C4	.922	.944	.933	.979	.941
	Y1	.911	.911	.933	.971	.941
	Y2	.989	.978	.967	.988	.961
	Y3	.967	1.000	.944	.999	.919
	Y4	.944	.944	.967	.988	.980
200	A1	.978	.989	.989	.983	.974
	A2	.956	.967	.933	.994	.931
	A3	.978	.989	.978	.989	.986
	A4	.989	1.000	.967	.982	.951
	B1	.911	.922	.889	.962	.892
	B2	.900	.911	.867	.952	.856
	B3	.900	.922	.933	.966	.952
	B4	.967	.967	.978	1.000	.972
	C1	.967	.978	.956	1.000	.951
	C2	.911	.956	.900	.954	.889
	C3	.911	.922	.922	.971	.927
	C4	.944	.967	.956	.989	.958
	Y1	.922	.933	.944	.979	.956
	Y2	.978	.967	.978	.989	.972
	Y3	.967	.967	.944	.998	.927
	Y4	.956	.956	.967	.996	.969
500	A1	.967	.978	.978	.992	.983
	A2	.967	.978	.944	.993	.941
	A3	.967	.967	.978	.993	.988
	A4	1.000	1.000	.989	.980	.983
	B1	.956	.967	.967	.998	.974
	B2	.956	.956	.944	.993	.939
	B3	.967	.967	.956	.998	.953
	B4	.978	.978	.978	.989	.980
	C1	.967	.978	.956	.992	.952
	C2	.922	.944	.911	.972	.913
	C3	.933	.933	.944	.986	.942
	C4	.956	.956	.967	.991	.973
	Y1	.956	.956	.967	.999	.973
	Y2	.978	.978	.978	.991	.978
	Y3	.978	.989	.956	.988	.949
	Y4	.956	.956	.956	.997	.964

Note: Values in bold indicate unacceptable bias estimate

The loading for Model 1 was set as 0.7 for every item underlying the respective constructs. Table 1 shows the results for Model 1. Among the CB-SEM estimators, SFLS consists of 5 and ML consists of 4 low CBI values (< 0.8) indicators for a small sample size (n = 50). GLS consisted of 9 low CBI values (< 0.8) indicators. PLS generates better CBI values in most of the indicators, compared to PLSc and CB-SEM estimators when the sample size is small. This result implies that at a low sample size (n = 50), CB-SEM estimators (ML, GLS, SFLS) generated several biased indicators loading estimates similar to PLSc because the latter mimics a CB-SEM estimator (Dijkstra & Henseler, 2015). Contrarily, CB-SEM estimators comprised of only 1 to 3 low CBI values (< 0.8) indicator when the sample size increased (n = 100). This finding attests that CB-SEM estimators require at least 100 sample sizes to produce good estimates. This finding was also applicable to PLSc. At a large sample size ($n \geq 200$), ML and GLS do not consist of any undesirable bias estimates (<0.8). Surprisingly, there seem to be no undesirable bias estimates (<0.8) in PLS. A thorough observation of CBI values show that GLS produces a better estimate compared to ML and PLS in most indicators, with CBI values closer to 1.0. As the sample size increases (i.e., n = 500), none of the estimators in CB-SEM and PLS-SEM generate any undesirable bias estimates (<0.8). A closer look at their CBI values reveals that for large sample sizes, the CB-SEM estimators produce a high value compared to PLS-SEM. This finding proves that PLSc requires a large sample ($n \geq 100$) to generate a better estimate. The biasness of indicator loading estimates in ML, GLS, SFLS, and PLSc at a low sample size might be due to their underestimation compared to PLS. The indicator loadings estimated by the CBI for Model 2 is shown in Table 2. Every item loading underlying the respective constructs for Model 2 was set as 0.8. Based on the results, CB-SEM estimators consist of merely 1 low CBI value (< 0.8) except GLS at a low sample size (n=50), similar to PLSc. Interestingly, PLS does not produce any undesirable bias estimates (<0.8) across all sample sizes (n=50, 100, 200, 500). In a large sample (n ≥ 200), the total number of low bias indicator estimates (CBI >0.9) in GLS and SFLS is higher than ML, indicating that the use of other estimation methods can be considered despite ML being appropriate for large sample sizes. Similarly, PLS and PLSc estimate indicator loadings with high CBI values (>0.9) across large sample sizes (n=200, 500). For Model 3, every item loading underlying the respective constructs was set as 0.9. The result is shown in Table 3. Among CB-SEM estimators, it is reported that ML does not produce any undesirable bias estimates (<0.8) for a low sample size. Having said that, at low sample size, ML shows a better CBI performance than PLS for Model 3. Meanwhile, PLSc consists of 4 low CBI values (< 0.8) indicators, indicating that among other estimators, PLSc generates several unacceptable bias estimates (<0.8). For 100 sample sizes, we observed a contradictory finding where ML generates 1 unacceptable bias estimate (<0.8) and conversely for PLS. At the same time, other estimators in CB-SEM and PLS-SEM consist of 1 low CBI values (< 0.8) indicator. In a large sample (n ≥ 200), ML and PLS produce low bias estimates (>0.9) in all indicators.

4. Discussion

The current study examined the performance of several estimation methods in terms of CBI values. We used simulation to create data with various sample sizes employing a simple model following specific criteria (e.g., normal, complete data). Based on the findings, we derive some conclusions. As stated, the true loadings of indicators for the three models are homogenous between 0.7 to 0.9. At sample size 50, where the items' true indicator loading was set as 0.7, PLS consists of only 1 low CBI value and therefore performs markedly better than PLSc and CB-SEM estimators. However, at sample size 100, ML and GLS generate 1 unbiased indicator loading estimate while PLS shows consistent results. At sample size $n \geq 200$, ML, GLS, and PLS do not consist of any low CBI values. Therefore, we infer that when data of true loading 0.7 is to be simulated, the study can be conducted by using GLS as an alternative fitting function in CB-SEM and PLS estimator.

For Model 2, PLS is capable of providing accurate estimates for all the sample sizes. This finding suggests that PLS produces unbiased estimation across all sample sizes when the actual indicator loading is high (i.e. 0.8). In contrast, PLSc and CB-SEM estimators proved to perform notably better when the indicator loadings are high (i.e. 0.8) across large sample sizes (n = 100, 200, 500). However, among all the estimators for Model 3, ML does not comprise low CBI values (<0.8) and PLSc produces several biased loading estimates at a low sample size. Meanwhile, GLS, SFLS, and PLS were observed to generate 1 biased loading estimate, suggesting that when a population indicator loading is high (e.g., 0.9), ML estimation's performance is superior compared to others. Contrarily, at 100 samples, ML shows inconsistent results; it consists of 1 low CBI value (<0.8). However, the CBI for each loading indicator using PLS is high, with no low CBI values found over large sample sizes ($n \geq$ 100).

From the findings, we can conclude that when true indicator loadings are high (i.e. 0.9), the indicator loadings are underestimated and therefore fall within the range of acceptable bias. At large sample sizes ($n \geq 200$), we infer that when it refers to simulation study with the population indicator loadings greater than 0.8, one can consider using CB-SEM and PLS-SEM estimators to generate better parameter estimates. An indicator loading value of 0.8 indicates great internal consistency (Rahlin et al., 2019). If the true indicator loadings are 0.7, ML, GLS, and PLS are better alternatives for a large sample size ($n \geq 100$). Consistent with Aimran et al. (2017a), when the actual indicator loadings are consistently high (e.g., ≥ 0.8), PLS can be considered as a good estimator. The biases of indicator loading estimates in ML, GLS, SFLS and PLSc at low sample size might be due to its underestimation compared to PLS. The findings of this study also prove that for the cases of 50 samples and the true indicator loading being extremely high (e.g., 0.9), PLSc clearly underestimates the true value of indicator loading, thus producing unacceptable bias estimates. This issue may have arisen due to the consequences of measurement error propagation on parameter estimates (Afthanorhan et al., 2021). When estimating the indicator loadings for confirmatory purposes, one should consider using CB-SEM rather than PLSc because the former produces more accurate estimates for indicator loadings (Afthanorhan et al., 2020).

This study is not without limitations. The comparison of this model's implementations to CB-SEM and PLS-SEM is not certainly expected to be generalized to all models because the conclusions are derived from the model within the scale of this study. However, such will raise scholars' awareness of several critical issues that may emerge and should be pondered when choosing the relevant SEM technique for their research.

5. Conclusion

From this study, we conclude that PLS is a good estimator if the actual indicator loadings are consistently high (e.g., ≥ 0.8). The biases of indicator loading estimates in ML, GLS, SFLS, and PLSc at low sample size might be due to its underestimation compared to PLS. On the other hand, the indicator loadings are underestimated hence fall within the permissible bias range when true indicator loadings are high (i.e., 0.9).

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