An Extensive Comparison Between CBSEM and Consistent PLS-SEM On Producing the Estimates of Construct Correlation in Applied Research

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Abstract. Structural Equation Modelling (SEM) is always recognized as the method of choice across research fields when involving multiple construct, observed variables and relationships. However, there are a very few studies had investigated the SEM efficiency on producing the construct correlation. Thus, the Monte Carlo simulation was conducted on two different methods (CBSEM and Consistent PLS) using different sample size and model. The findings revealed that the CBSEM is performed consistently than Consistent PLS when the model being tested is in factor. The recommendations also provided to guide the SEM users.

Keywords: CBSEM, Consistent PLS, Construct Correlation, Monte Carlo

1. Introduction
Consistent PLS is well-known as composite modeling that uses linear combination item to produce loadings on their respective construct [1-2]. The Consistent PLS used adjusted correlation matrix in OLS estimation where the beta coefficients can be driven from this equation. The correlation matrix is corrected for attenuation of PLS method using the novel reliability estimates ([3-5] to produce a consistent estimator. These studies correctly observe that Consistent PLS is succeed to produce consistent estimate than those of PLS-PM, but it biasedness actually never proven in any article.

This problem should be touched in a simulation works for determining to how accurate the estimation of construct correlation produced by Consistent PLS using varies of population models. If not, the results appeared from Consistent PLS is vague and untrusted. Because PLS method has demonstrated overestimate the true construct correlation which would lead to capitalize strongly on chance correlation [6]. The capitalization on chance means the true correlation that do not exist in the population, but are non-zero in a sample because of sample variability [7]. Its presences due to the effects of propagation of measurement errors. But in the case of Consistent PLS, this issue has been resolved [8] which means the capitalization issue may not exist. Nevertheless, the position a Consistent PLS method is cannot be assisted by the fact or hearsay but must be proven in a simulation as purpose of this study.
2. Findings
The Monte Carlo simulation was used to compare the performance of CBSEM and Consistent PLS method using different sample size and model. The sample size involves 50, 100, 200 and 500 whereas the three established model was chosen from social sciences areas (TRA, Loyalty and UTAUT). The data was generated using R software and then the analysis for CBSEM and Consistent PLS were performed using AMOS and ADANCO software respectively. The results were shown in the following tables.

| MODEL | CORRELATION | CB-SEM | Consistent PLS |
|-------|-------------|--------|----------------|
|       |             | 50     | 100 | 200 | 500 | 50 | 100 | 200 | 500 | 50 | 100 | 200 | 500 |
| X1 <- X2 | .891 | .620 | .673 | .572 | .628 | .400 | .453 | .382 |
| X1 <- M1 | .625 | .541 | .657 | .654 | .451 | .374 | .434 | .444 |
| X1 <- Y | .383 | .671 | .569 | .650 | .375 | .427 | .388 | .443 |
| X1 <- M3 | .872 | .447 | .690 | .525 | .610 | .319 | .453 | .350 |
| X1 <- M2 | .771 | .572 | .625 | .620 | .536 | .389 | .435 | .423 |
| X2 <- X1 | .541 | .506 | .441 | .464 | .357 | .355 | .297 | .317 |
| X2 <- Y | .409 | .387 | .528 | .419 | .314 | .272 | .356 | .274 |
| X2 <- M3 | .637 | .423 | .443 | .419 | .477 | .304 | .298 | .277 |
| X2 <- M2 | .666 | .276 | .544 | .391 | .441 | .309 | .400 | .270 |
| M1 <- Y | -. | .446 | .328 | .336 | .368 | .320 | .221 | .240 |
| M1 <- M3 | .176 | .060 | .283 | .357 | .258 | .072 | .181 | .241 |
| M1 <- M2 | .626 | .245 | .400 | .295 | .384 | .219 | .278 | .204 |
| Y <- M3 | .168 | -. | .107 | .131 | .183 | .193 | -. | .093 | .122 |
| TRA |        |       |      |      |      |      |      |      |
| X1 <- X2 | .845 | .685 | .649 | .733 | .631 | .569 | .540 | .583 |
| X1 <- M | .990 | .556 | .602 | .518 | .814 | .448 | .511 | .430 |
| X1 <- Y | .974 | .585 | .655 | .624 | .773 | .546 | .612 | .550 |
| X2 <- M | .329 | .469 | .423 | .501 | .255 | .337 | .306 | .334 |
| X2 <- Y | .721 | .614 | .651 | .723 | .577 | .467 | .478 | .510 |
| M <- Y | .224 | .087 | .364 | .233 | .208 | .078 | .278 | .173 |
| LOYALTY |        |       |      |      |      |      |      |      |
| X1 <- X2 | .805 | .740 | .593 | .639 | .609 | .501 | .404 | .439 |
| X1 <- X3 | .903 | .747 | .725 | .633 | .567 | .468 | .446 | .437 |
| X1 <- Y | .559 | .879 | .704 | .645 | .415 | .647 | .512 | .475 |
| X1 <- M | .756 | .568 | .678 | .712 | .555 | .352 | .463 | .492 |
| X1 <- X4 | .892 | .565 | .656 | .510 | .641 | .342 | .431 | .338 |
| X2 <- X3 | .496 | .598 | .409 | .466 | .432 | .397 | .284 | .322 |
| X2 <- Y | .273 | .435 | .394 | .510 | .243 | .356 | .289 | .384 |
| X2 <- M | .673 | .591 | .474 | .372 | .519 | .423 | .351 | .271 |
| X2 <- X4 | .665 | .505 | .389 | .385 | .545 | .299 | .266 | .252 |
| X3 <- Y | .265 | .482 | .267 | .341 | .162 | .350 | .186 | .258 |
| X3 <- M | .247 | .408 | .475 | .438 | .263 | .237 | .319 | .310 |
| X3 <- X4 | .543 | .412 | .506 | .219 | .426 | .262 | .325 | .155 |
| Y <- M | .090 | .241 | .216 | .172 | .035 | .175 | .166 | .138 |
| Y <- X4 | .449 | .110 | .305 | .203 | .382 | .104 | .220 | .150 |
| M <- X4 | .410 | .527 | .267 | .186 | .327 | .333 | .194 | .136 |

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Table 1 showing the result of construct correlations for every model with varying of sample size between CBSEM and Consistent PLS for the cases in which the population parameter is set using the values proposed. The purpose of this analyses is to assess the estimates of construct correlation have on the model when the latent variables have been intercorrelated where the model consistent with the reality. That is, the data should be consistent with the model designed [9]. Based on this reason addressed, the study wish to set the construct correlation and then being compare with the estimation techniques. As such, the discrepancy between those of CBSEM and Consistent PLS can be addressed for examine in which estimation technique is competent to produce the result equivalent to the real situations. This, the result of raw bias of construct correlation are performed for verify of this assessment (see Table 2).

| ESTIMATION METHOD | CB-SEM | Consistent PLS |
|-------------------|--------|-----------------|
| MODEL            | CORRELATION |             |             |
|                  | 50   | 100  | 200  | 500  | 50    | 100  | 200  | 500  |
| X1 <-> X2        | 0.37 | -0.05 | 0.04  | -0.12 | -0.03 | -0.38 | -0.30 | -0.41 |
| X1 <-> M1        | -0.41 | 0.03  | -0.12 | 0.00  | -0.42 | -0.34 | -0.40 | -0.32 |
| X1 <-> Y         | 0.34  | -0.31 | 0.06  | -0.19 | -0.06 | -0.51 | -0.30 | -0.46 |
| X1 <-> M2        | 0.19  | -0.12 | -0.04 | -0.05 | -0.18 | -0.40 | -0.33 | -0.35 |
| X2 <-> M1        | 0.20  | 0.12  | 0.02  | 0.03  | -0.21 | -0.21 | -0.34 | -0.30 |
| X2 <-> Y         | -0.09 | -0.14 | 0.17  | -0.07 | -0.30 | -0.40 | -0.21 | -0.39 |
| X2 <-> M3        | 0.42  | -0.06 | -0.02 | -0.07 | 0.06  | -0.32 | -0.34 | -0.38 |
| X2 <-> M2        | 0.48  | -0.39 | 0.21  | -0.13 | -0.02 | -0.31 | -0.11 | -0.40 |
| M1 <-> Y         | -1.01 | 0.27  | -0.06 | 0.04  | 0.05  | -0.09 | -0.37 | -0.31 |
| M1 <-> M3        | -0.50 | -0.83 | -0.19 | 0.02  | -0.26 | -0.79 | -0.48 | -0.31 |
| M1 <-> M2        | 0.79  | -0.30 | 0.14  | -0.16 | 0.10  | -0.37 | -0.21 | -0.42 |
| Y <-> M3         | 0.12  | -1.71 | -0.13 | 0.22  | 0.29  | -1.52 | -0.38 | -0.19 |
| Y <-> M2         | 0.61  | -0.44 | -0.13 | -0.16 | 0.53  | -0.53 | -0.36 | -0.40 |
| M3 <-> M2        | 1.10  | -0.35 | 0.16  | 0.01  | 0.70  | -0.27 | -0.18 | -0.33 |
| TRA               |       |       |       |       |       |       |       |       |
| LOYALTY           |       |       |       |       |       |       |       |       |
| X1 <-> X2        | 0.30  | 0.05  | 0.00  | 0.13  | -0.03 | -0.12 | -0.17 | -0.10 |
| X1 <-> M1        | 0.80  | 0.01  | 0.09  | -0.06 | 0.48  | -0.19 | -0.07 | -0.22 |
| X1 <-> Y         | 0.62  | -0.03 | 0.09  | 0.04  | 0.29  | -0.09 | 0.02  | -0.08 |
| X2 <-> M3        | -0.34 | -0.06 | -0.15 | 0.00  | -0.49 | -0.33 | -0.39 | -0.33 |
| X2 <-> Y         | 0.03  | -0.12 | -0.07 | 0.03  | -0.18 | -0.33 | -0.32 | -0.27 |
| M1 <-> Y         | 0.12  | -0.57 | 0.82  | 0.17  | 0.04  | -0.61 | 0.39  | -0.14 |
| X1 <-> X3        | 0.24  | 0.14  | -0.09 | -0.02 | -0.06 | -0.23 | -0.38 | -0.32 |
| X1 <-> X4        | 0.39  | 0.15  | 0.12  | -0.03 | -0.13 | -0.28 | -0.31 | -0.33 |
| X1 <-> Y         | -0.14 | 0.35  | 0.08  | -0.01 | -0.36 | 0.00  | -0.21 | -0.27 |
| X1 <-> M3        | 0.16  | -0.13 | 0.04  | 0.10  | -0.15 | -0.46 | -0.29 | -0.24 |
| X1 <-> X4        | 0.37  | -0.13 | 0.01  | -0.22 | -0.01 | -0.47 | -0.34 | -0.48 |
| X2 <-> X3        | 0.10  | 0.33  | -0.09 | 0.04  | -0.04 | -0.12 | -0.37 | -0.28 |
| X2 <-> Y         | -0.39 | -0.03 | -0.12 | 0.13  | 0.46  | -0.21 | -0.36 | -0.15 |
| X2 <-> M3        | 0.50  | 0.31  | 0.05  | -0.17 | 0.15  | -0.06 | -0.22 | -0.40 |
| X2 <-> X4        | 0.48  | 0.12  | -0.14 | -0.14 | 0.21  | -0.34 | -0.41 | -0.44 |
| X3 <-> Y         | -0.24 | 0.38  | -0.24 | -0.03 | -0.54 | 0.00  | -0.47 | -0.26 |
| X3 <-> M3        | -0.29 | 0.17  | 0.36  | 0.25  | -0.25 | -0.32 | -0.09 | -0.11 |
| X3 <-> X4        | 0.55  | 0.18  | 0.45  | -0.37 | 0.22  | -0.25 | -0.07 | -0.56 |
| Y <-> M3         | -0.40 | 0.61  | 0.44  | 0.15  | -0.77 | 0.17  | 0.11  | 0.08 |
| Y <-> X4         | 0.80  | -0.56 | 0.22  | -0.19 | 0.53  | -0.58 | -0.12 | -0.40 |
| M <-> X4         | 0.64  | 1.11  | 0.07  | -0.26 | 0.31  | 0.33  | -0.22 | -0.46 |
In terms of the consistency approach for construct correlations, both of those estimation methods are performed well for estimating the parameter estimates as the sample size increases. It can be confirmed by the finding revealed of the three established models. This, however, for CBSEM technique, the consistency properties are achieved when the sample size above 100. To add, the bias of construct correlation is occurred when the sample size at 50 as being addressed by these three models which is generally cannot be trusted. This is because the values of the construct correlation at sample of 50 is too high and it is may severely suffered of the bias estimation (upward). To confirmed of this comments, the result of raw bias of construct correlation is explained in detailed where most of the construct correlation values are higher than 0.20 or 20% for all models. Other than that, the problem of eigenvalues estimates of construct correlation for CBSEM is seem exist in the TRA model (M1<->Y = -1.01). The values of construct correlations with CBSEM have being standardized from the variance-covariance matrix, thereby, the values of the construct correlation must not be higher than 1.0.

The detrimental effects of bias also occurred with Consistent PLS but it is not harmed of the standardized problem where all the values of construct correlations are sensible (i.e: the value in the range of 0.0 to 1.0). Nevertheless, the negativity sign of parameter estimates under Consistent PLS is largely exist in the three models at sample size of 50. In the simulation design, this study set all the construct correlation in the form of positively sign which means the direction of latent variable correlations are positive signal. It should be noted that the bias can affect not only the regression weight and standardized estimates but also of other predictors in the model (Kline, 2016; McDonald, Behson & Seifert, 2005).

This is because the presence of propagation of measurement error falsify the direction of parameter estimates and thus the estimates may be biased upward (too large) or downward (too small) or attenuation bias. In this case, the author expect the CBSEM has a problem of upward bias and Consistent PLS has a downward bias or attenuation bias when involves of small samples.

For the cases of 100 samples and above on TRA model, the CBSEM is absolutely best equipped to solve the detrimental effects of bias when the estimation of construct correlation is approach towards the true values. These findings against of what estimation lies for Consistent PLS where the bias effects are remained occurred in the model. The values of bias effect become negatively large deviate from the true values of construct correlations. Then, the next step is to consider on Loyalty and UTAUT model which depict the same analysis for construct correlations with unequal probabilities. In these models, the Consistent PLS maintained to produce negative sign of parameter estimates with varying of sample size. Surprisingly, the result for UTAUT model in terms of the construct correlations perspectives is widely negative sign that is belief Consistent PLS underestimates the construct correlations across samples.

In dissimilarity, the CBSEM did not have the problems of negative sign of construct correlation because virtually all the model performed in the current study does not show the presence of the attenuation bias. Rather, the Consistent PLS is much more problematic when the sign effect is totally occurred for all models specifically UTAUT model. Generally, the Consistent PLS did not developed for correction of bias in partial least square context but it is more on mimic CBSEM to produce the consistent estimates across samples [3-5]. It should be reminded that if the sign of the coefficients is incorrect presence in the model, it means that the multicollinearity problem may exist in the model. With the problem of sign coefficients addressed, the discriminant validity based Fornell-Larcker criterion would be affected.

1 The statistics r for correlation estimates has a theoretical maximum absolute value of 1.0 [10]. If statistic r higher than 1.0 exist in the model, it maybe because of the problem of measurement error, extreme scores or outlier in the model. In order to ensure the model free from these effects, the adequate of sample size is necessary. Please keep in mind that the adequate of sample size is tied with the power analyses to reject the false model.

2 Multicollinearity exist if independent variables are related to each other. Generally, when two or more independent variables are related to each other, then at least one or more variables are redundant because of their tendency to contribute overlapping information. As such, the result obtained is cannot be trusted when the information obtained have being shared.
3. Discussion and Conclusion

The Consistent PLS used adjusted correlation matrix in OLS estimation where the beta coefficients can be derived from this equation. The correlation matrix is corrected for attenuation of PLS method using the novel reliability estimates which is based on the estimated loadings [5] to produce a consistent estimator but it is not without problem (consistent construct correlations: \( r_{ij} = \frac{r_{ij}}{\sqrt{P_A(e) P_A(e)}} \)).

First, this study showed that the effects of latent variable correlation is decreases as the sample size increases, which making Consistent PLS has negatives biased estimator where CBSEM does not. Indeed, Consistent PLS is consistent in all level when using disattenuated correlations. This consistency is not happening with CBSEM when apply to small samples, but this effect is reduced to an admissible solution when the observation reached to 100 samples. Although Consistent PLS is seem even consistent at small samples, but their downwards bias (attenuation bias) is high for estimating the construct correlations.

It should be note that to declare one of the specified method is at least has a priori knowledge for both measurement and structural model without concentrate merely on consistency estimates. What it means is that the model should be formed by the existence evidence. In this sense, Consistent PLS pertain to situations where the overall nomological network has been well understood and established [11]. Based on this, the latent variable correlation is discussed to find out how well this correlation has been disattenuated.

\[
R^2(n_i, n_j) = \left( \frac{\lambda_i}{\lambda_i + \lambda_j} \right) \quad \text{ (Equation 1)}
\]

Clearly, the squared correlation, \( R^2 \) between a population proxy and its corresponding latent variable is equal

\[
R^2(n_i, n_j) = \frac{\lambda_i^2}{\lambda_i + \lambda_j} \quad \text{ (Equation 2)}
\]

This squared correlations are related with the size of model and their high quality indicators. This correlation can be close to one once the model has large number of latent variables, manifest variables with high quality of indicator [12] where this is the characters of PLS that only being consistent at large (Wold, 1982). The important algebraic relationships can be deduced

\[
R^2(n_i, n_j) = R^2(n_i, n_k) \cdot R^2(n_k, n_j) \quad \text{ (Equation 3)}
\]

This indicates that the Consistent PLS will tend to underestimate the squared correlations between latent variables [5]. Because the proxies can never replicate the latent variable exactly as is shown in Equation (Equation 3). With this properties, this is questionable to declare Consistent PLS is useful for confirmatory modeling. Most of psychological researchers attributed that the confirmatory modeling can be identified with the presents of replication. The squared correlation can be estimated consistently by:

\[
p_{ij}^2 = \frac{R^2(n_i, n_j)}{R^2(n_i, n_l) \cdot R^2(n_j, n_l)} \quad \text{ (Equation 4)}
\]

For this reason, the latent variable correlation with Consistent PLS is always smaller than those of CBSEM. Therefore, the estimates of latent variable correlations produced by Consistent PLS is tend to have negative bias. To bolster this claim, the result between two competitors as depicted in Table 1 and Table 2. The results clearly showed Consistent PLS clearly underestimate the true value of latent variable correlations. If the nomological network by Consistent PLS is too small even in correct situations, then, this specified method is not reasonable for confirmation oriented.

The reason for this problem is may occurred due to effects of propagation of measurement error that not only affect the parameter estimates but also their construct correlations [10]. In many literatures, the attenuation of correlation due to effects of measurement error is directly proportional to the size of the population model correlations [13]. For this justification, this study using three

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3 Upwards bias of correlation can be happen in the sample data due to the effects of random error. The random error or chance factor is exist because of the sample variability [7] which tendency to amplify the construct correlation making the capitalization on chance is occurred. [14] defines capitalization on chance as seizing on the properties of samples.
population models with different number of construct correlations. Among of these three population models, the Loyalty model which is the fewest construct has less affected by the effects of measurement error. That is, the effects of capitalization on chance is not only decreases with increasing of sample size but also the size of construct correlations.

Another reason for this occasions is the effects of positively biased reliability estimates could cancel out the capitalization on chance, resulting in negligible overall bias [13]. In reality, [4], [7] and [15] found that the traditional PLS has faced the problem of capitalization on chance correlation where it means that correlation that do not exist in the true populations, but are non-zero in a sample. The capitalization on chance with PLS is beneficial to ensure the model being tested free from the presence of downwards bias [16]. As such, improving or fixing PLS by corrected for attenuation is not reasonable here for estimating the construct correlation in the case of confirmatory purpose. Because the Consistent PLS now has faced the problem of attenuation bias. It should be noted that the values of beta coefficients are related with the value of construct correlations. At last, if the construct correlation is too small, then, the beta coefficient produced is become small (proportional to the size of correlations) and eventually the significant effect under null hypothesis significant testing is affected.

The Consistent PLS is indeed works well performing consistent construct correlations but the problem of bias is still remained. With the presence of bias in an estimator due to effects of measurement error, it is possible to over or underestimate the true value of populations [17] which means explanation for justify the model is correctly causally specified is not rationale. According to Hair et al [2], the composite method facilitates accounting the measurement error thus making PLS is superior. Such claims are not reasonable because the measurement error checks had not been programmed into the software (SMARTPLS 3.0 and ADANCO 2.0).

To propose further correction to Consistent PLS, it should augment the correlated measurement errors in order to completely matching CBSEM estimation [18]. Other than that, the error in variable regression (EIV) is also relevant for this situation to overcome the problems of measurement error, capitalization on chance and biased reliability [19-22].

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