

Five Common Mistakes for Using Partial Least Squares Path Modeling (PLS-PM) in Management Research

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ABSTRACT

The value of Partial Least Squares Path Modeling (PLS-PM) in management research has now been acknowledged, although the PLS-PM was developed for a reason. First, the PLS-PM was developed as an alternative to Covariance based Structural Equation Modeling (CBSEM) when exploratory research is conducted. As far as this method concerned, many researchers are misused or overuse the application of PLS-PM without understanding the basic knowledge in structural equation modeling. Thus, the purpose of this paper is to discuss the five common mistakes (data distributions, sample size limitations, unsatisfactory fitness index, misunderstanding between confirmatory and exploratory research, and poor factor loadings) for using PLS-PM over CB-SEM in management research. We concluded that the researchers should respect these methods and justify their use when conducting the research projects because some of the projects might be better for CB-SEM or PLS-PM.

Keywords: PLS-PM, CBSEM, Exploratory research, Structural Equation Modeling

INTRODUCTION

In the past few years, the marketing and management research has been a substantive increase in the number of submissions, dissertations, journals, and publications using Partial Least Square Path Modeling (PLS-PM) techniques (Aimran et al., 2017; Afthanorhan et al., 2018) as displayed in Figure 1. In this analysis, we included keywords related to PLS-PM to better understand the substantive research topic of interest. This recent increase might be due to the increasing number of friendly statistical packages such as SmartPLS, PLS Gui SaaS, WarpPLS, VisualPLS, XLSTATPLS, SPADPLS, Adanco, and PLS Graph. Another reason could be the increased relevant resources explaining its application, such as Hair et al. (2019), Ghasemy et al. (2020), and Ringle et al. (2019).



Figure 1 Word Cloud of the Keyword of the Top Field Using PLS-PM

The PLS-PM was also recognized as the composite factor method as the method generates the parameter estimates from the linear combination of manifest variables in the construct. In contrast, the Covariance Based Structural Equation Modeling (CBSEM) that exemplified in several statistical packages such as AMOS, LISREL, Mplus, EQS, and Lavaan known as the common factor method. Both of them are differently used, as depicted in Table 1. Dijkstra & Henseler (2015) reported that PLS-

PM was declared as the most prominent approach among the composite factor method because it can assist the applied researchers to handle complex modeling without the presence of stringent assumption which contradicts what CBSEM has (Zainol et al., 2019; Afthanorhan et al., 2019).

Table 1 *Common Factor and Composite Factor Method*

Common Factor Method	Composite Factor Method
Maximum Likelihood-based CBSEM (ML-CBSEM)	Partial Least Squares Path Modeling (PLS-PM)
Diagonal Weighted Least Squares (DWLS-CBSEM)	Generalized Structure Component Analysis (GSCA)
Weighted Least Squares Maximum Variance (WLSMV-CBSEM)	Consistent PLS (PLSc)
Asymptotic Distribution Free (ADF-CBSEM)	Weighted PLS
Generalized Least Squares (GLS- CBSEM)	PLS Predict
Statistical Software	
AMOS	SmartPLS
LISREL	ADANCO
MPLUS	Warp PLS
LAVAN	PLS Graph
EQS	PLS Gui

In the historical roots, PLS-PM was formulated by Herman Wold in 1982 that is recognized as an alternative to the CBSEM method (Wold, 2004). This, however, PLS-PM was viewed as not appropriate for statistical tools in empirical research as it has serious implications for model specifications, absence of measurement error, biasedness of indicator loadings and weight, biasedness of construct correlation, lacking global fitness index, and improper solution to bootstrapping techniques (Antonakis et al., 2010; Vandenberg, 2006; Ronkko & Evermann, 2013; Aguirre-Urreta & Marakas, 2014; McIntosh et al., 2014; Goodhue, Lewis & Thompson, 2012; Aguirre-Urreta & Ronkko, 2018). Such previous researches are addressed allegedly insurmountable flaws associated with the use of PLS-PM and go so far as to explicitly and implicitly call for a ban and condemn their use.

Nevertheless, Lohmoller (1989) and Henseler, Hubona, & Ray (2016) claimed that PLS-PM remains relevant if the study is accompanying with exploratory purpose or

misspecification of the measurement model. The misspecification measurement model can be identified if the applied researchers are not sure about the causal effect between exogenous and endogenous constructs. The exploratory purpose is defined if the applied researchers are not having possible literature theories or evidence to support the model proposed. More precisely, the PLS-PM was proper for predicting rather than estimating the relationships between latent variables or construct in a hypothesized model. Although PLS-PM was known for exploratory purpose since its inception yet, some of the applied researchers elucidated that PLS-PM can fix with the confirmatory or exploratory purpose (Ringle et al., 2018; Sarstedt et al., 2016; Schubert, Henseler, & Dijkstra, 2018). Throughout their discussions, the method of PLS-PM is apparently accepted in many journals or publications for confirmatory purposes as it uses an established theory for testing.

Since then, the debate on the true nature of PLS-PM was endless, specifically on statistical methodologies. Unfortunately, articles on statistical flaws within PLS-PM are not considered seriously, and its usefulness is repeatably used in all situations. To be clear, many applied researchers were overuse PLS-PM in management research. The applied researcher should bear in mind that there are a time and place for PLS-PM or CBSEM that we can use for data analysis. For this example, there are times in which PLS-PM is can or cannot be applied in management research rather than encouraging it to be a method of choice in various domains. Therefore, it would be better if the applied researchers can understand the concept of PLS-PM and know when it can be used to examine a research model.

In other words, the researchers are just as lackadaisical about selecting the appropriate approach in SEM as they seem inclined to handle less stringent assumptions. Compared with standard CBSEM, the statistical assumptions are even more complicated as the Maximum Likelihood estimator is always preferred. As such, the applied researcher's opined PLS-PM indeed was a 'silver bullet' method without an attempt to understand the statistical underpinnings. The intractable publications using PLS-PM are actually questionable because the estimates yielded from that analysis may not be compatible with the model proposed as PLS-PM naturally developed for exploratory sense. Consequently, one can be sure that many publications in the confirmatory sense with PLS-PM are improper solutions which mean most of the previous findings was not meet the current dynamics progress. With this consistent thinking, Dijkstra & Henseler (2015) consent to label PLS-PM under exploratory sense. They admitted PLS-PM technique could not be relevant for confirmatory studies, but it can be appropriate if the factor correlations are corrected. Thus, they introduced new coefficient reliability in the conjunction of PLS-PM to provide consistent path coefficients and indicator loadings that are seemed suitable for confirmatory studies.

The impressive development in PLS-PM, so-called Consistent Partial Least Square (PLSc), was declared more powerful than PLS-PM (Dijkstra & Scmerlleh-engel, 2014).

Although PLSc is maybe better than PLS-PM, yet, the improvement in the conjunction of PLS algorithm associated with factor correlations just manages to produce consistent estimates and indicator loadings that are always debated for many ages. In fact, there are more other statistical flaws present in its application that are still unresolved. Thus, it is too early to note PLSc tenable as CBSEM to accommodate well in the confirmatory approach that seeks accurate estimates of one variable's effects on another variable (Bollen & Diamantopoulos, 2017). To be part of the confirmatory approach, the method adopted should comply with several statistical assumptions so that the results produced are not harmed (improper solutions). In particular, the procedures related to the confirmatory approach must take into account the measurement error, measurement effect, consistent indicator loadings, consistent factor correlations, global fit indexes, disturbance of the endogenous variables, and high statistical power (tended to reject poor models). Among these, PLSc is lags far behind those of CBSEM in many perspectives.

Turning back to the discussion on PLS-PM, more researchers believe PLS-PM was capable as CBSEM to adapt well as a confirmatory approach. Yet, this faithful is contravene with the recent seminal work by Dijkstra & Henseler (2015). Accordingly, PLS-PM was only relevant if the models were classified under exploratory sense, and PLSc is superior to accommodate both characters, whether in the exploratory or confirmatory sense. Yet, the interpretation confounding within PLS-PM in behavioral sciences has remained unclear. Instead, this is not a good time to propose PLSc technique if the controversy relies upon PLS-PM was kept abandoned. Therefore, it is a serious problem if the researchers are continuously misused structural equation models in the research methodology. Align with this background, the purpose of the present article is to address each possible situation that leads the researchers to adopt PLS-PM technique. Our ultimate aim is to advance our understanding to the readers of which situations are necessary for PLS-PM technique so that results revealed for managerial decisions are valid.

Foundation of PLS-PM

Historically, PLS-PM was developed as an alternative to CBSEM when the study related is too complicated and lacks literature theories (Fornell & Bookstein, 1982). Herman Wold introduced it in the early of 1970, but its inception was debated due to some limitations applied in PLS-PM. Nevertheless, its performance has been improved in the early 2000 by the proponent of PLS-PM, as shown in Figure 1.

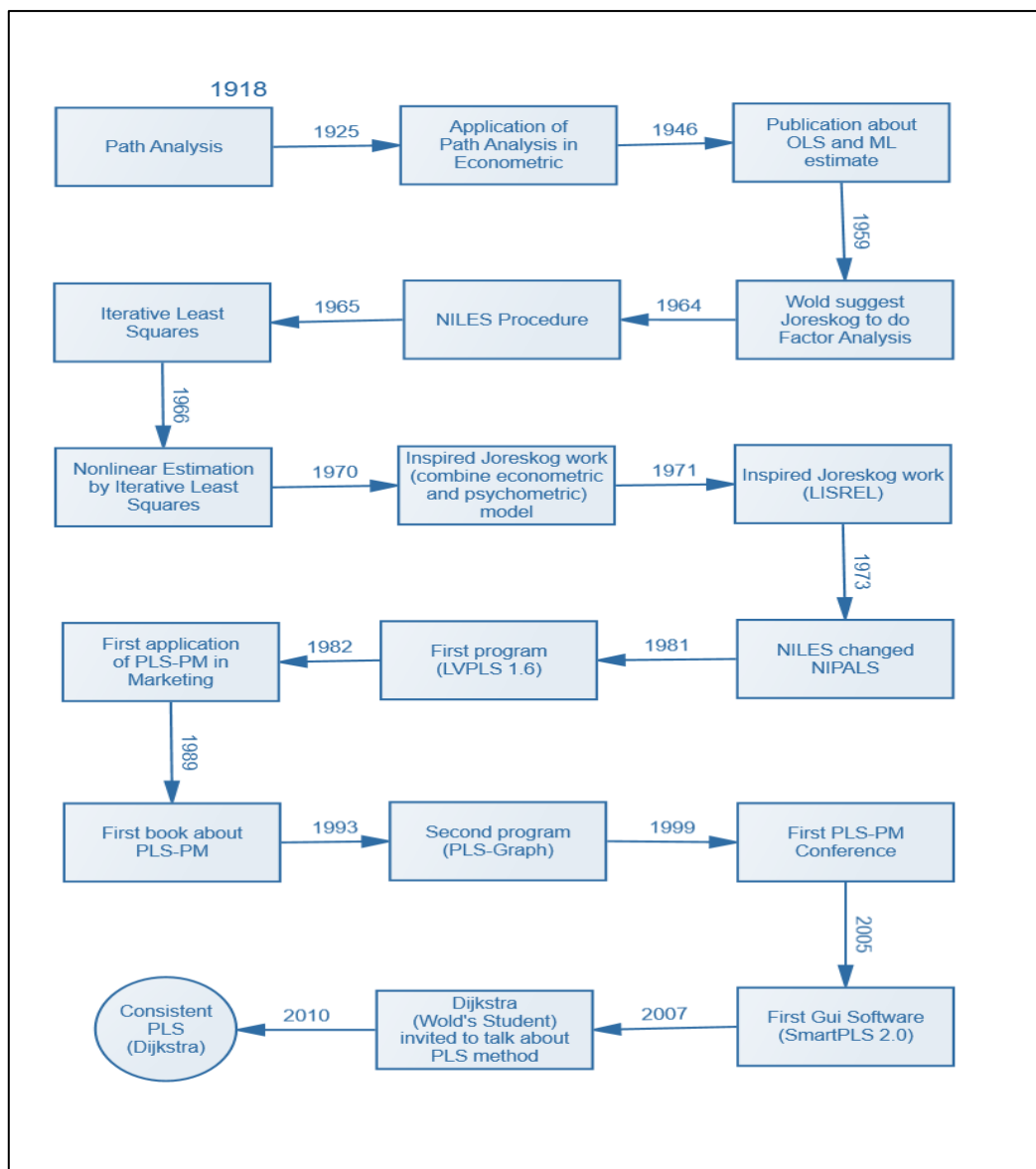


Figure 1 *Development of PLS-PM*

To be clear, PLS analysis can be viewed as one of the composite approaches that adopt one strategy of estimating a latent variable as a component or weighted composite of indicators (Takane & Hwang, 2017; Hwang, Takane, & Tenenhaus, 2015). In contrast, the established method as CBSEM adopts a strategy of estimating a latent variable as a common factor of indicators (Bollen, 2011; Bollen & Noble, 2011). In this regard, PLS-PM can be considered a composite-based structural equation modeling. Meanwhile, CBSEM can be trusted as a common factor-based structural equation modeling.

Composite-based structural equation modeling actually has three known approaches: regression on sum scales, generalized structured component analysis, and

PLS analysis. All of these approaches using a limited information estimator (e.g., ordinary least square) to obtain the path coefficient and indicator loadings with the help of the iterative algorithm to minimize the criterion function. Among these approaches, only PLS analysis needs two steps which called internal (component with indicators) and external (causal between latent variables) estimation that is prior to estimating the path coefficients (Hwang, Takane, Tenenhaus, 2015; Ronkko, McIntosh & Antonakis, 2015; Ronkko et al., 2016). It was believed composite is the only rationale for the exploratory purpose because PLS (composite approach) estimates a more general model than CBSEM and is less affected by model misspecification or poor model in some parts of the model. Basically, the estimates obtained were meaningless if the common factor model was incorrectly, and thus the common factor is always viewed as a confirmatory tool (Antonakis et al., 2010). Furthermore, the composite factor model relaxes the strong assumption that all the covariation between the manifest variables' block is explained by a common factor method (Henseler, Ringle, & Sarstedt, 2015). This means that the composite factor does not impose any restrictions on the covariance between manifest variables of the same latent variables. Therefore, PLS-PM has advantages over CBSEM to handle non-normal data, fewer indicators per construct, possible to include a larger number of indicators, assumes all measured variance is useful for prediction, small sample size, and fitness index is not determined.

With this regard, most the applied researchers are interested in PLS-PM attractiveness since its inception. Compared with standard CBSEM, the researchers must conduct the path analysis and confirmatory factor analysis independently to make the estimates derived reliable. To do so, researchers face the difficulty to fix the latent variables constitute under CBSEM. That is, the interpretation model must be include model testing, model validation, and model fit. All of these models are prior to achieving each construct's validity, and it is only can be presented with CBSEM.

Furthermore, global fit statistics nested in CBSEM are aimed to measure the magnitude of indicators loadings and other model parameters in a complementary fashion when assessing the measurement models. Such models do not exist in PLS-PM, which is why PLS-PM was considered an exploratory tool since it is much more flexible than CBSEM. This point may illustrate that the PLS-PM is prioritized for the exploratory approach only. As mentioned earlier, the study aims to describe what possible situations that encourage the applied researchers to elect PLS-PM rather than CBSEM.

Fundamental of PLS-PM

For the management research, these updated methodologies achievement in PLS-PM can benefit the applied researchers as it can model the nomological network by expressing the relationships between constructs in a single research model. According to Hair et al. (2019) and Sarstedt et al. (2020), the PLS-PM was the full-fledged method that has many advantages over the CBSEM. These advantages are shown in the following table about PLS-PM properties.

Table 2 *PLS-PM Properties*

No.	Condition	Explanation
1.	Sample size requirement	According to Chin (1999), PLS-PM can handle at least 20 sample sizes. Generally, the PLS-PM can achieve a high level of statistical power with small samples
2.	Data distribution	No distributional assumptions are needed. Thus, PLS-PM method works well with non-normal data distributed.
3.	Measurement scale	PLS-PM can work with a categorical and continuous scale
4.	Number of items per construct	PLS-PM easily handle more than 50 items per construct as the method can generate the latent variable score for estimation purpose.
5.	Model conceptualization	PLS-PM easily incorporates formative and reflective construct simultaneously
6.	Model complexity	Can handle complex model with many structural relationships and items per construct.
7.	Model identification	PLS-PM does not have model identification to generate the parameter estimates
8.	Measurement model assessment	PLS-PM has a limited number of global fitness index and can delete many items
9.	Structural model assessment	PLS-PM provides the predictive relevance (Q^2) and effect size (f^2) result for the targeted construct
10.	Efficiency	The results can be obtained after a few iterations.

REVIEW ON THE CRITICAL SITUATION WHEN APPLYING PLS-PM

Mistake 1: Data Distribution

PLS-PM was always perceived as the best choice in structural equation models when the researchers have to deal with non-normal data. Because PLS-PM was developed on the basis of the non-parametric assumption that is no stringent assumption is necessary for estimating the path coefficient of the structural model. Consequently, the applied researchers believe adopting PLS-PM is not a serious issue in the research methodology in that it is well developed to control multiple variables concurrently. This belief should not be allowed in the quantitative methodology. Because every method developed actually has its own objective and purpose of assuring the research requirement can be satisfied. The main reason PLS-PM is flexible than those of CBSEM was induced the ordinary least square estimator is utilized to derive the path coefficients of measurement and structural model. That estimator relaxes the strong covariation between blocks of indicator that cannot be visualized in the model (Henseler, Hubona, & Ray, 2016). As such, the PLS-PM was viewed as a composite factor method that is appropriate for exploratory sense.

In the previous research, most of the published paper debunks that CBSEM is one of the parametric approaches that is the normality data should be considered in the first place. In order to make sure the statistical assumptions that constitute under CBSEM is achieved, they assure the normality data can be maintained. In fact, there are more simulation study believe CBSEM is totally robust against the departure of normality. It can be verified by Bollen (1989) and Jöreskog & Sörbom (1989) through their simulation studies based on non-normal data. Further, Yuan & Bentler (1998) contend that maximum likelihood estimator-based structural equation modeling is able to yield consistent path coefficients of the structural model from the minimum sample size of 50. The problem here is that the outcome of standard error cannot be conserved, and thus the supplementary approach is necessary as the bootstrap approach accompanies a maximum likelihood estimator to stabilize the standard error. Thereby, the existence of non-normal data can actually be remedied by applying those approaches to ensure the path coefficients of the structural model are proper.

Other than that, the researchers can attempt another estimator such as asymptotic distribution-free, which is the requirement for normal data was neglected. Because asymptotic distribution-free was not part of Consistent Asymptotic Normality (CAN), that is the normality assumption is prior to the best fit for path coefficient of structural

model (Anderson & Gerbing, 1988). It can be inferred that traditional structural equation modeling is actually able to handle both types of normal and non-normal.

Mistake 2: Sample Size Limitation

The sample size requirement for structural equation modeling was frequently one of the problematic issues for many ages. Because there is more recent literature that decides the minimum requirement for sample size, the minimum sample size required should be more than 100 of sample size (Hoyle, 1995; Byrne, 2016; Aziz et al., 2019). Accordingly, those sample size was tailored to the nature of structural equation modeling to ensure the result revealed represents the actual population. Other than that, it can help the analyst to resort to structural equation modeling produce findings free from the presence of improper solutions and non-convergence of path coefficients (Anderson & Gerbing, 1988; Marsh, Wen, & Hau, 2004; Fan, Thompson & Wang, 1999; Chen et al., 2001). Furthers, some of the literature affirmed that the size of the model (number of indicator per factor) influence the effects of estimation method (Ding, Velicir, & Harlow, 1995; Kline, 2015; Loehlin, 1998; Marsh, Hau & Balla, 1998) and it was believe become one of the common practice lately for those whom interest to structural equation modeling as their resolution. Thereby, an unreasonable sample size (below than 100 of sample size) resulting in the researchers leading to another convenience approach that is not necessary for high samples.

As such, the PLS-PM may be preferable to those of CB-SEM if the researchers deal with such insufficient sample size when testing the relationship between latent variables. For researchers, obtaining high samples may provide a great challenge, specifically when their research scope was restricted. For these reasons, the researchers believe PLS-PM is prioritized over CBSEM. The simulation studies verify that PLS-PM is superior under conditions of small sample size and violation of data distribution (Chin et al., 2003; Haenlein & Kaplan, 2004) where the estimation of the structural model is unaffected, which means remain proper solutions for decision.

Although PLS-PM seemed better than CBSEM in terms of the sample size perspective, the estimation method remains as the composite factor, which means the result derived is acceptable under exploratory sense only (see Goodhue, Lewis & Thompson, 2006 for distinguishing between common factor and composite factor). Other than that, the model specified was invalid and cannot proceed with testing the hypothesized model. Moreover, the PLS-PM was touted as able to handle the complex relationships as sample size as 20 (Chin & Newstedt, 1999), and it is the reason what leads the researchers to choose PLS-PM over CBSEM when it comes to the small samples.

The reason for choosing PLS-PM when involves a small sample is prohibited as the estimation method was actually developed, not resolving the sample issue. In statistics underpinning, population sampling is the process of a select subset of subjects or respondents that is representative of the entire population (Polkinghorne, 2005). The estimation obtained based on population sampling must be reflected with the actual population to ensure the real estimates are worth the research. To ensure such estimation is worthy, the sufficient sample size is necessary for statistical methodologies that involve a structural equation model approach.

The structural equation modeling approach for small sample size and the sample's minimum requirement remains questionable, although more studies discuss this issue (Herzog & Boomsma, 2009; Lai & Kelley, 2011; Bentler & Yuan, 1999). It is because of using the maximum likelihood estimator as one of the preferable estimators limiting the ability of structural equation modeling. Therefore, the best solution for small samples is to collect sufficient data and ensure the variable involves in the model has high quality. The researchers may adopt a strategy of enhancing items' quality through Item Response Theory (IRT; Embretson & Reise, 2013; Lord & Wingersky, 1984; van der Linden & Hambleton, 2013) in the first place before subsequent to the analysis phase. On another typical occasion, the researchers may delete low-quality variables by scrutiny their value of factor loadings as recommended by Hair et al. (2019). Accordingly, the strength of factor loading is differ depending on the sample size requirement. Apart from that, the use of item parceling in the model may be beneficial for this situation since the sample size requirement is tied to the model's size (Landis, Beal, & Tesluk, 2000; Ronkko & Evermann, 2013). One conclusion can be made that the issue of sample size in the handling of structural equation modeling should be discontinued. Thus, such a plea is not admissible for researchers to switch to PLS-PM.

Table 3 *Significance Factor Loading based on Sample Size*

Factor Loading	Sample Size needed for Significance
0.30	350
0.35	250
0.40	200
0.45	150
0.50	120
0.55	100
0.60	85
0.65	70
0.70	60
0.75	50

Source: Hair et al. (2019)

Mistake 3: Unsatisfactory of fitness index

In structural equation modeling practice, the fitness model should be reported to reflect on how well the model being researched. It can be identified with the fitness index such as Chi-square normalized by degree of freedom (Chisq/df), Root Mean Square Error Approximation (RMSEA), Comparative Fit Index (CFI), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), and Normed Fit Index (NFI) as shown in Table 4. All of this fitness should be complying with the threshold values as it believes capable of identifying a misspecified model that cannot be proven by PLS-PM (McIntosh et al., 2014). To ensure the model can be tested with the covariance-based structural equation model, the researcher must confirm the fitness model through Confirmatory Factor Analysis (CFA). The CFA can be driven by two measurement models such as individual measurement and pooled measurement model. Among these, the pooled measurement model is much better than the other ones as it can take account of two indicators per factor and latent variable correlations (Chong, Nazim, & Ahmad, 2014).

This, however, the fitness index may not be completely satisfied when the researchers utilize the CFA technique. Because the required level for each fitness index is excessively high for research requirement as the parsimonious index (Chisq/df < 3.0), absolute index (RMSEA < 0.08), and incremental index (CFI, IFI, TLI, NFI > 0.90). Generally, the model may have jeopardized if the model involves a great number of size variables and latent variables (Hair et al., 2017). Therefore, the measurement model's unsatisfactory fitness index can be one of the primer substances that pushes the researchers to move on to the other approach as PLS-PM that compromises with great help. Theoretically, the common factor adopted in the covariance structural equation

model entails one of the strong literature and evidence, which means the model must be truly established. Apart from that, common method bias may affect the measurement fitness as the questionnaire was not familiar with the study's scope. Therefore, the assessment for common method bias becomes an interesting method to ascertain the applied researchers detecting the item problem. So far, there are three approaches available for examining the method bias, namely Harman Single-factor, common latent factor, and marker variables. Among them, Harman single factor is the most prominent technique across the field as it is very convenient and understandable. Thus, avoiding CB-SEM use due to improper fitness is not compromising the results for hypothesis testing can be trusted. Because selecting the wrong method for data analysis can lead to the wrong conclusions.

Table 4 *Fitness Indexes*

Categories	Fitness Index	Recommended values
Absolute Fit Index	Chi-square	$P > 0.05$
	Root Mean Square Error Approximation (RMSEA)	< 0.08
	Goodness of Fit	> 0.90
Incremental Fit Index	Adjusted Goodness of Fit (AGFI)	> 0.90
	Comparative Fit Index (CFI)	> 0.90
	Tucker-Lewis Index (TLI)	> 0.90
	Normed Fit Index (NFI)	> 0.90
Parsimonious Fit Index	Chi-square/degree of freedom	< 5.0

Mistake 4: Misunderstanding between Confirmatory and Exploratory Research

While PLS-PM has been frequently used across research fields, but there are not many previous studies clearly explain the distinction between confirmatory and exploratory research. Many scholars claimed their study using PLS-PM because it works well with both confirmatory and exploratory research. It is important to know that confirmatory and exploratory research is different and have their own assumptions that need to be fulfilled. As a matter of fact, Ioannidis (2005) pointed out that most research findings are false. Thus, wrong results can lead to the wrong conclusion and eventually impacted the decisions.

According to Wagenmakers et al. (2012), sciences and social sciences can be bad in many ways, such as faulty logic, flawed design, and misuse of statistical analysis. The erroneous statistical method has gained increasing recently in management research, as explicitly addressed by Guide & Ketokivi (2015). Confirmatory theory proceeds from a priori hypotheses concerning some topic of interest (Jaeger & Halliday, 1998) to test those hypotheses. Most research programs rely on inductive to prove the alternative hypothesis can be true. For many instances, research has shown that applied researchers interest in seeking confirmation rather than exploration (Nickerson, 1998). In other words, it can help the researchers to gain some confidence in the validity of those hypotheses.

In contrast, the exploratory research using beta error (type II error rate) indicates that there is no significant effect even though the effect actually existed in the true population (Willaby et al., 2015; Rönkko & Evermann, 2013). Thus, exploratory research can be used to generate a hypothesis rather than testing the hypothesis. It should be noted that exploration is usually used to gain new insight from which new hypotheses might be developed (James & McCullosh, 1985). It is fruitful for prediction purposes or examining the potential relationships between constructs in a single model. Though Rigdon (2014) pointed out that the nature of the confirmation model can be changed if the researchers use different established theories in a single model, it should be noted that the measured item remains the same. It means that the idea to claim the model is in exploratory research not achieved as the original items are used to assess the construct (measurement model).

Henseler (2017) contemplated that the characteristics of the construct can determine the character of the research design. Accordingly, any factors that describe the behavioral construct should be examined with CBSEM (confirmatory method), while design-construct should be tested with PLS-PM (exploratory method). These distinctions could help the applied researchers to understand confirmation and exploration better, as summarized in table 5.

Table 5 *Different between Confirmatory and Exploratory Research*

CONFIRMATORY	EXPLORATORY
Replicating an established theory into a new domain - Confirming a pre-specified relationship	Develop a new model based on lack of evidence or fact - Connecting ideas to understand cause-effect
For estimating purpose Statistically significant results Definitive answers to hypotheses	For prediction purpose Potential relationships Novel relevant questions
For theory-driven Hypotheses testing methods Highest accuracy numerical models	For data-driven
For theory testing Testing a priori hypotheses Maximizing the confidence in conclusions	For theory development (exploration purpose) Developing promising a posteriori hypothesis Designing efficient experiments Reinforcing confirmed conclusion
For the common factor model	For the composite factor model
Modified the existing theory by included a new path or construct	Entirely changing the measurement item in existing theory
Integrating theory	Change the relationships between construct from prior theories (reciprocal relationships)
Behavioral construct (attribute and attitudes)	Design construct (designer design the construct)
Example: Customer Satisfaction, Customer Loyalty, Trust, Distrust, Attitudinal, Communication, Affective, Emotion, Leadership, Performance	Example: Brand equity, Type of system, Information source, Decision-making perspective, Network structure, Network capability, Technology, Device, Location

Mistake 5: Poor Factor Loadings

One of the essential approaches in SEM method is determining the value of factor loading for each construct. In CBSEM, this method was known as Confirmatory Factor Analysis (CFA), whereas in PLS-PM, the method was recognized as Confirmatory Composite Analysis (CCA). Both methods are used to evaluating the measurement model, but the ways for estimating the model are different. The value of factor loading is allowed for the reflective construct to assist the applied researcher in identifying the measured item's suitability under construct.

According to Awang et al. (2015) and Afthanorhan et al. (2019), the minimum value of factor loading is 0.60, although some other resources also accept the value of factor loading at least 0.50. This practice partially similar to PLS-PM but much more convenient as not many fitness indexes were deployed. Hair et al. (2019) suggested that the acceptable item loading is 0.708, but the researcher can consider another item loading between 0.40 and 0.70 as long as the AVE and CR are achieved. This reliability and validity are sensitive to the number of items per construct and the value of factor loading, as depicted in Table 6. It showed that the higher factor loading is, the higher value of AVE and CR are.

Nevertheless, many applied researchers move to PLS-PM because the loadings usually obtained larger than the value of factor loading from CBSEM. The AVE and CR can be achieved from this advantages as it is part of the measurement model assessment. It should be noted the value of item loading from CBSEM is considered as factor loading, whereas in PLS-PM, it was called composite loading. Thus, the researchers should be consistent with one method after knowing the character of the model.

Table 6 Rule of Thumb for Factor Loadings and AVE and CR

Number of Items	Factor Loading	AVE	CR	Comment
2	0.60	0.360	0.529	AVE and CR not achieved
	0.75	0.563	0.720	AVE and CR achieved
	0.90	0.810	0.895	AVE and CR achieved
4	0.60	0.360	0.692	AVE and CR not achieved
	0.75	0.563	0.837	AVE and CR achieved
	0.90	0.810	0.945	AVE and CR achieved
6	0.60	0.360	0.771	AVE not achieved
	0.75	0.563	0.885	AVE and CR achieved
	0.90	0.810	0.962	AVE and CR achieved
8	0.60	0.360	0.818	AVE not achieved
	0.75	0.563	0.911	AVE and CR achieved
	0.90	0.810	0.972	AVE and CR achieved
10	0.60	0.360	0.849	AVE not achieved
	0.75	0.563	0.928	AVE and CR achieved
	0.90	0.810	0.977	AVE and CR achieved

CONCLUDING REMARKS

PLS-PM and CB-SEM generate the parameter estimates differently and offer different settings for the applied researchers. There are times where we want to understand the behavior of the fitness index. There are also times when we really want to handle the non-normal data and small sample size. We can get different findings from different methods, not because one method is good and another one is bad, but those methods actually approach the data using different philosophies.

If you are a good researcher, you will know to make a decision when analyzing the data, and if you are not familiar with these concepts and arguments, then we would encourage you to read the research papers from “*Organizational Research Methods*,” *Structural Equation Modeling*” journal and articles cited in the reference list. From here, the researchers can learn how the usefulness of PLS-PM and CB-SEM, then create a value judgment on which method is more relevant for your quantitative research analysis.

For those of you that overuse PLS-PM in management research, be careful about moderating the hater's statements by justifying the choice to use PLS-PM. We also strongly encourage you to consider CB-SEM technique as it might be a better tool for some of your research projects (Asnawi et al., 2019). Be sure to understand the PLS-PM and CB-SEM, then use them properly as both of them can complement each other in data analysis. There also have several prominent researchers have now acknowledged the value of PLS-PM technique. Evidently, many top-tier journals in the management field accept the use of PLS-PM technique, and an extension of PLS methods such as efficient PLS, consistent PLS, weighted PLS, and PLS prediction are now introduced to cater to the limitation of traditional PLS-PM. We believe this paper can stimulate the SEM users to respect PLS-PM and CB-SEM techniques to accept the variety of research methods.

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