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Partial Least Squares Structural Squation Modeling (PLS-SEM) Analysis for Social and Management Research : A Literature Review

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ABSTRACT

Many social and management studies use quantitative methods that use partial least sound. The purpose of this article is to explain the sequence and standard of data processing using partial least squares for social and management research. The method of writing this article is to review articles written by Hair. The results of the explanation of this article can help researchers to process and analyze data with partial least squares. PLS is an acronym for Partial Least Square. Broadly speaking, PLS is a measuring tool in statistical methods. PLS is a multivariate technique that is capable of managing various things such as response variables to explanatory variables simultaneously. From the initial explanation, it is clear how PLS brings convenience to those who master it.Actually, PLS is an alternative in statistics

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Abstract

Introduction

In a study, researchers are often faced with conditions where the sample size is large enough, but has a weak theoretical basis in the relationship between the hypothesized variables. However, it is not uncommon to find relationships between variables that are very complex, but the data sample size is small. Partial Least Square (PLS) is an alternative method of Structural Equation Modeling (SEM) that can be used to overcome these problems. There are two approaches in Structural Equation Modeling (SEM), namely covariance-based SEM (Covariance Based-SEM, CB-SEM) and SEM with variance approach (VB-SEM) with Partial Least Squares (PLS-SEM) technique. PLS-PM has now become a popular analytical tool with many international journals or scientific research using this method. Partial Least Square abbreviated as PLS is a type of component-based SEM analysis with formative construct properties. PLS was first used to process data in the field of econometrics as an alternative to SEM techniques with a weak theoretical basis. PLS only serves as a predictor analysis tool, not a model test.

According to Hair et al.(2019) currently covariance-based structural equation modeling (CB-SEM) is the dominant method for analyzing complex interrelationships between observed variables and latent variables. In fact, until around 2021, far more articles published in social science and management journals use CBSEM than partial least squares structural equation modeling (PLS-SEM). In recent years, the number of articles published using PLS-SEM has increased significantly compared to CB-SEM (Hair

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et al., 2017). PLS-SEM is now widely applied in various social science disciplines, including organizational management (Sosik et al., 2009), marketing management (Bernarto et al.2020), international management (Richter et al., 2015), human resource management (Ringle et al., 2019), management information systems (Ringle et al., 2012), operations management (Peng and Lai, 2012), education management (Asbari et al., 2021), education management (Purwanto et al.2021) marketing management (Hair et al., 2012), management accounting (Nitzl, 2016), strategic management (Hair et al., 2012), hospitality management (Ali et al., 2018) and supply chain management (Kaufmann and Gaeckler, 2015). Several textbooks (e.g., Garson, 2016; Ramayah et al., 2016), edited volumes (eAvkiran and Ringle, 2018; Ali et al., 2018), and special editions of scientific journals (Rasoolimanesh and Ali, 2018; Shiau et al., 2019) describe PLS-SEM or propose methodological extensions (Hair et al.2019).

Methode

The method of writing this article is a literature review, namely reviewing articles from several articles, naley

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Result and Discussion

According to Hair et al.(2019) the PLS-SEM method is of great interest to many researchers because it allows estimating complex models with many constructs, indicator variables, and structural paths without imposing distributional assumptions on the data. PLS-SEM is a predictive causal approach to SEM that emphasizes prediction in estimating statistical models, the structure of which is designed to provide causal explanations (Wold, 1982; Sarstedt et al., 2017). According to Hair et al.(2019) this technique thus overcomes the apparent dichotomy between explanations as usual emphasized in academic research and prediction, which is the basis for developing managerial implications (Hair et al., 2019). In addition, there are easy-to-use software packages that generally require little technical knowledge of the method, such as PLS-Graph (Chin, 2003) and SmartPLS (Ringle et al., 2015; Ringle et al., 2005), while more complex for statistics Computing software environments, such as R, can also run PLS-SEM (e.g. semPLS; Monecke and Leisch, 2012). Writers such as Richter et al. (2016), Rigdon (2016) and Sarstedt et al. (2017) provide a more detailed argument and discussion about when to use and not to use PLS-SEM (Hair et al .2019).

According to Hair et al.(2019) the reason the researcher chose PLS-SEM is when the analysis relates to testing the theoretical framework of predictive perspective, when the structural model is complex and includes many constructs, indicator or relationship models, when the aim of the research is to better understand increasing complexity by exploring theoretical extensions of an already established theory (exploratory research for theory development, when the path model includes one or more constructs formatively measured, when research consists of financial ratios or similar types of data artifacts, when research is based on secondary/archive data, which may lack comprehensive evidence on the basis of measurement theory, when small population limits sample size, PLS-SEM also works particularly well with large sample sizes, when distributional issues are a concern, such as a lack of normality; and when the study requires scores of latent variables for follow-up analysis.The list above provides an overview of points to consider when deciding whether PLS is an SEM method. appropriate for a study.

According to Hair et al.(2019) PLS-SEM offers solutions with small sample sizes when the model consists of many constructs and a large number of items (Fornell and Bookstein, 1982; Willaby et al., 2015; Hair et al., 2017).Technically, the PLS-SEM algorithm makes this possible by computing measurements and structural model relationships separately, rather than simultaneously. Arstedt et al. (2016) summarize how PLS-SEM provides a solution when methods such as CB-SEM develop unacceptable or inconsistent results with complex and small models and sample sizes, regardless of whether the data come from a generalized model or a composite population. According to Hair et al.(2019) PLS-SEM can certainly be used with smaller samples but the nature of the population dictates situations where small sample sizes are acceptable (Rigdon, 2016).Assuming that other situational characteristics are the same, the more heterogeneous the population, the larger the sample size required to achieve an acceptable sampling error (Cochran, 1977).

According to Hair et al.(2019) many researchers have benefited from the high level of statistics of this method compared to CB-SEM (Reinartz et al., 2009; Hair et al., 2017). Greater statistical power means that PLS-SEM is more likely to identify relationships as significant when they are indeed present in the population (Sarstedt and Moi, 2019). PLS-SEM characteristics of higher statistical power are useful for exploration research that examines underdeveloped or still developing theories.

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The first step in evaluating PLS-SEM results involves examining the measurement model. The relevant criteria differ for reflective and formative constructs. if the measurement model meets all the necessary criteria, the researcher then needs to assess the structural model (Hair et al., 2017). Like most statistical methods, PLS-SEM has a rule of thumb that serves as a guide for evaluating model results (Chin, 2010; Götz et al., 2010; Henseler et al., 2009; Dagu, 1998; Tenenhaus et al., 2005; Roldán and SánchezFranco , 2012; Hair et al., 2017). The reliability value for exploratory research should be at least 0.60, while the reliability for studies that depend on the established size should be 0.70 or higher.

The first step in the assessment of the reflective measurement model involves examining the loading indicators. Loading above 0.708 is recommended, as it indicates that the construction explain more than 50 percent of the variance of the indicator, thus providing an acceptable item of reliability.The second step is to assess the reliability of internal consistency, most often using Jöreskog's (1971) composite reliability. A higher value generally indicates a higher level of reliability. For example, a reliability value between 0.60 and 0.70 is considered acceptable in exploration In the study, values between 0.70 and 0.90 ranged from "satisfactory to good." Values of 0.95 and higher are problematic, as they indicate that the item is redundant, thereby reducing construct validity (Diamantopoulos et al., 2012; Drolet and Morrison, 2001). A reliability value of 0.95 and above also indicates a possible unwanted response pattern.

According to Hair et al.(2019) researchers can use bootstrap confidence intervals to test whether construct reliability is significantly higher than the recommended minimum (eg the lower limit of the 95 percent confidence interval of construct reliability is higher than 0.70) .Similarly, they can test whether construct reliability is significantly lower than the maximum recommended threshold (eg the upper limit of the 95 percent confidence interval of construct reliability is lower than 0.95). To obtain a bootstrap confidence interval, in line with Aguirre-Urreta and Rönkkö (2018), researchers generally have to use the percentile method. According to Hair et al.(2019) the third step of the assessment of the reflective measurement model discusses the convergence of the validity of each construct measure. Convergent validity is the extent to which the construct converges to explain the variance of the items. The metric used to evaluate the constructs of convergent validity is the average extracted variance (AVE) for all items in each construct. According to Hair et al.(2019) To calculate the AVE, we must square the loading of each indicator on a construct and calculate the mean value. average. An acceptable AVE is 0.50 or higher indicating that the construct explains at least 50 percent of the variance of the items.

According to Hair et al.(2019) the fourth step is to assess discriminant validity, namely the extent to which the construction is empirically different from other constructs in the structural model. Fornell and Larcker (1981) proposed traditional metrics and suggested that each AVE construct should be compared with the correlation between the quadratic constructs of the same construct and all other reflectively measured constructs in the structural model. The joint variance for all model constructs cannot be greater than their AVE. According to Hair et al.(2019) recent research shows that this metric is not suitable for assessing discriminant validity. For example, Henseler et al. (2015) show that the FornellLarcker criteria do not perform well, especially when the indicators loading on the constructs are only slightly different (eg all indicator loadings are between 0.65 and 0.85). Instead, Henseler et al. (2015) proposed a heterotrait-monotrait ratio (HTMT) correlation (Voorhees et al., 2016). The HTMT is defined as the mean value of item correlations across constructs relative to the mean (geometric) correlations for items measuring the same construct. The discriminant validity problem is present when the HTMT value is high. Henseler et al. (2015) proposed a threshold value of 0.90 for structural models with conceptually

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very similar constructs, for example cognitive satisfaction, affective satisfaction and loyalty. In such a setting, an HTMT value above 0.90 would indicate that discriminant validity does not exist. According to Hair et al.(2019) But when the constructs are conceptually more different, a lower, more conservative threshold value is suggested, such as: 0.85 (Henseler et al., 2015). In addition to these guidelines, bootstrap can be applied to test whether the HTMT value is significantly different from 1.00 (Henseler et al., 2015) or a lower threshold value such as 0.85 or 0.90, which should be determined based on contextual research (Franke and Sarstedt, 2019). More specifically, the researcher can check whether the upper bound of the 95 percent confidence interval of HTMT is lower than 0.90 or 0.85. According to Hair et al.(2019) Variance inflation factor (VIF) is often used to evaluate the formative collinearity of indicators. A VIF value of 5 or more indicates a critical collinearity problem among indicators formatively measured constructs. However, collinearity problems can also occur at lower VIF values of 3 (Mason and Perreault, 1991; Becker et al., 2015). Ideally, the VIF value should be close to 3 and lower. . According to Hair et al. (2017), indicators with insignificant weights must definitely be omitted if the weighting is also not important. Low but significant loadings of 0.50 and below indicate that one should consider remove indicators, unless there is strong support for their inclusion on the basis of measurement theory.

According to Hair et al.(2019) Structural model coefficients for the relationship between constructs are derived from estimating a series of regression equations. Before assessing the structure of the relationship, collinearity should be checked to ensure unbiased regression of the results. According to Hair et al.(2019) This process is similar to assessing the formative measurement model, but the latent variable score of the predictor construct in partial regression is used to calculate the VIF value. VIF values above 5 indicate possible collinearity problems among predictor constructs, but collinearity problems can also occur at VIF values lower than 3-5 (Mason and Perreault, 1991; Becker et al., 2015). Ideally, the VIF value should be close to 3 and lower. If collinearity is a problem, a frequently used option is to create a higher order a model that can be supported by theory (Hair et al., 2017). According to Hair et al.(2019) If collinearity is not a problem, the next step is to examine the R Square value of the endogenous construct. According to Hair et al.(2019) R Square measures the variance, which is described in each endogenous construct and is therefore a measure of the explanatory power of the model (Shmueli and Kopius, 2011). R Square is also referred to as the predictive power in the sample (Rigdon, 2012). The R Square ranges from 0 to 1, with higher values indicating greater explanatory power. As a guideline, R Square values of 0.75, 0.50 and 0.25 can be considered substantial, moderate, and weak (Henseler et al., 2009; Hair et al., 2011). Acceptable R Square values are based on context and in some disciplines R Square values as low as 0.10 are considered satisfactory, for example, when predicting stock returns (Raithel et al., 2012)

According Hair et al.(2019) Researchers can also assess how deletion of certain predictor constructs affects the f Square value of endogenous constructs. This metric is f Square effect size and is a bit redundant with the size of the path coefficient. More precisely, the ranking order of relevance predictor constructs in explaining the dependent construct in a structural model is often the same when compare the path coefficient size and f Square effect size. In such a situation, f Square effect sizes should only be reported if requested by the editor or reviewer. If the rank order of construct relevance, when describing the dependent construct in the structural model,different when comparing path coefficient sizes and f Square effect sizes, researchers can report f Square effect sizes to explain the presence of, for example, partial or full mediation (Nitzl et al., 2016). As a rule of thumb, values higher than 0.02, 0.15 and 0.35 represent small, medium and large f effect size (Cohen, 1988).

Complex modeling often uses structural equation modeling (SEM) with various conditions that must be met. In some modeling these conditions are sometimes difficult to fulfill. An alternative that can be chosen while still applying complex modeling is Partial Least Square (PLS). Here I will write down some of the reasons, a researcher chooses PLS. SEM is designed with the condition that there is strong theoretical support, while PLS modeling can be based on (1) theory, (2) empirical research results, (3) analogies, relationships between variables in other fields of science, (4) things normative, for example government regulations, laws and some, (5) other rational relations. So that the theoretical basis for PLS can be strong, weak and even exploratory.

Likewise with the measurement model, in PLS it is commonly known as the outer model, in SEM the relationship between indicators and variables is only reflexive, while in PLS it can be reflexive or formative. Determining indicators can be based on theory or adapting indicators that have been used by previous researchers. Assumptions about distribution are also an important requirement in SEM. The data in the modeling must meet the multinormal distribution, if this condition is not met then the estimate will be shifted to resampling or bootstrapping approaches. In PLS, the assumption of a multinormal distribution is not needed because the direct estimation uses bootstrapping technique. The sample size needed in SEM is quite large, in many references it is recommended to have 100-200 samples. While in PLS small samples (minimum 30-50) can be applied. Modification of the model to achieve better model feasibility is needed in SEM, while in PLS this is not necessary. In addition to these differences, there are several similarities between SEM and PLS, including: (1) the relationship between constructs is linear, (2) the model can be improved by using the "trimming theory" technique, namely eliminating paths that are not in the model, (3) a model fit calculation is required.

Reflective Measurement Model

Convergent Validity: convergent validity measures the magnitude of the correlation between constructs and latent variables.Individual Item Reliability: individual item reliability check, can be seen from the standardized loading factor value. The standardized loading factor describes the magnitude of the correlation between each measurement item (indicator) and its construct. The loading factor value > 0.7 is said to be ideal, meaning that the indicator is said to be valid in measuring the construct. In empirical research, the loading factor value > 0.5 is still acceptable. Thus, the loading factor value < 0.5 must be removed from the model (dropped). The squared value of the loading factor value is called communalities. This value shows the percentage of constructs able to explain the variations that exist in the indicator.

Internal Consistency or Construct Reliability: we see the internal consistency reliability of Cronbach's Alpha and Composite Reliability (CR) scores. Composite Reliability (CR) is better in measuring internal consistency than Cronbach's Alpha in SEM because CR does not assume the same weight of each indicator. Cronbach's Alpha tends to lower construct reliability than Composite Reliability (CR). The Composite Reliability (CR) interpretation is the same as Cronbach's Alpha. Limit values > 0.7 are acceptable, and values > 0.8 are very satisfactory.

Average Variance Extracted (AVE): Another measure of covergent validity is the Average Variance Extracted (AVE) value. The AVE value describes the variance or diversity of the manifest variables that

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can be owned by the latent construct. Thus, the greater the variance or diversity of the manifest variables that can be contained by the latent construct, the greater the representation of the manifest variable on the latent construct. Fornell and Larcker (1981) in Ghozali (2014:45) and Yamin and Kurniawan (2011:18) recommend the use of AVE for a criterion in assessing convergent validity. An AVE value of at least 0.5 indicates a good measure of convergent validity. That is, the latent variable can explain the average of more than half the variance of the indicators. The AVE value is obtained from the sum of the squares of the loading factor divided by the error. The AVE measure can also be used to measure the reliability of the latent variable component score and the results are more conservative than composite reliability (CR). If all indicators are standardized, then the AVE value will be the same as the average value of block communalities.

Discriminant Validity: the discriminant validity of the reflective model is evaluated through cross loading, then compares the AVE value with the square of the correlation value between constructs (or compares the square root of the AVE with the correlation between constructs). The measure of cross loading is to compare the correlation of the indicator with its construct and constructs from other blocks. If the correlation between the indicator and its construct is higher than the correlation with other block constructs, this indicates that the construct predicts the size of their block better than the other blocks. Another measure of discriminant validity is that the AVE root value must be higher than the correlation between constructs and other constructs or the AVE value is higher than the square of the correlation between the constructs.

Evaluation of Formative Measurement Models

There are at least five critical issues to determine the quality of the formative model, namely:Content specification, relates to the scope of the latent construct to be measured. This means that if you want to research, researchers must often discuss and guarantee the correct specification of the contents of the construct.Specification indicator, must clearly identify and define the indicator. The definition of indicators must go through clear literature and have been discussed with experts and validated with several pre-tests.
Reliability indicator, related to the importance of the indicators that make up the construct. Two recommendations for assessing the reliability of indicators are to look at the indicator signs in accordance with the hypothesis and the indicator weight is at least 0.2 or significant.Collinearity indicator, states that the indicators formed are not interconnected (very high) or there is no multicollinearity problem that can be measured by Variance Inflated Factor (VIF). A VIF value > 10 indicates there is a problem with multicollinearity, andExternal validity, ensures that all established indicators are included in the model.

Evaluation of the Inner Model (Structural Model)

After evaluating the construct/variable measurement model, the next step is to evaluate the structural model or inner model.

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The first step is to evaluate the structural model to see the significance of the relationship between the constructs/variables. This can be seen from the path coefficient which describes the strength of the relationship between constructs. The sign or direction in the path (path coefficient) must be in accordance with the hypothesized theory, its significance can be seen in the t test or CR (critical ratio) obtained from the bootstrapping process (resampling method).

The second step is to evaluate the value of R2. The interpretation of the value of R2 is the same as the interpretation of R2 of linear regression, namely the magnitude of the variability of endogenous variables that can be explained by exogenous variables. According to Chin (1998) in Yamin and Kurniawan (2011:21) the R2 criteria consist of three classifications, namely: R2 values 0.67, 0.33 and 0.19 as substantial, moderate (moderate) and weak (weak). Changes in the value of R2 can be used to see whether the effect of the exogenous latent variable on the endogenous latent variable has a substantive effect. This can be measured by the effect size f2. According to Cohen (1988) in Yamin and Kurniawan (2011:21) the suggested Effect Size f2 is 0.02, 0.15 and 0.35 with exogenous latent variables having small, moderate and large effects on the structural level.

To validate the overall structural model, Goodness of Fit (GoF) is used. The GoF index is a single measure to validate the combined performance of the measurement model and the structural model. This GoF value is obtained from the square root of the average communalities index multiplied by the average value of R2 model. GoF values range from 0 to 1 with the interpretation of values: 0.1 (small GoF), 0.25 (moderate GoF), and 0.36 (large GoF).

Another test in structural measurement is Q2 predictive relevance which serves to validate the model. This measurement is suitable if the Latin endogenous variable has a reflective measurement model. The results of Q2 predictive relevance are said to be good if the value > which indicates the exogenous latent variable is good (appropriate) as an explanatory variable that is able to predict the endogenous variable.

Like the analysis using CB-SEM, the analysis using PLS-SEM also uses two important stages, namely the measurement model and the structural model. The data in the measurement model is evaluated to determine its validity and reliability. Part of the measurement model consists of: (1). Individual loading of each question item. (2). Internal Composite Reliability (ICR). (3). Average Variance Extracted (AVE), and (4). Discriminant Validity.

Conclusion

PLS is an acronym for Partial Least Square. Broadly speaking, PLS is a measuring tool in statistical methods. PLS is a multivariate technique that is capable of managing various things such as response variables to explanatory variables simultaneously. From the initial explanation, it is clear how PLS brings convenience to those who master it.Actually, PLS is an alternative in statistics. PLS can be used for multiple regression analysis methods and principal component regression. Why is that? Because basically, these two methods are immune or their scientific language is robust. Robust itself means that the model parameters will not change much even though there are new samples taken from the total population.With the explanation above, it is very clear that PLS provides an interesting new alternative, which can be used for those of you who work with statistical methods because it will not bring difficult things into your work every day.PLS does not require as many assumptions or conditions as SEM so that it provides more meaningful convenience for you.PLS is actually used to design models only, but with the power of this analysis, you can also use it for theory confirmation.The use of PLS can be divided into two models, namely the inner model and the outer model. For the inner model, it is used for regression. While the outer model is used to test the validity and reliability.Compared to SEM or other similar ones, PLS is relatively simple. By using PLS, only two models are needed, namely the inner model and the outer model. This is what makes PLS simpler and easier to learn than others.

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