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KEY TO REPORTING PLS-SEM RESULTS

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ABSTRACT

Structural Equation Modelling (SEM) is predicated on the establishment of a causal relationship between endogenous and exogenous latent variables by measuring them with the help of indicators. These causal relationships, established on the basis of extant literature, are represented by a proposed research model, and hypotheses are designed and tested simultaneously. This method is usually analysed using covariance-based (CB-SEM) and variance-based (PLS-SEM) approaches. In numerous academic studies, the dominant approach for fitting and hypothesis testing of research models describing the relationships between latent variables has been the use of LISREL and AMOS software for covariance-based structural equation modelling. In recent years, there has been increase in the number of papers in which SEM analyses are performed with the PLS-SEM approach compared to CB-SEM. The present study commences with a discussion of CB-SEM and PLS-SEM, followed by the provision of straightforward and pragmatic guidance on the presentation of results in the context of PLS-SEM analysis, which constitutes the primary focus of the study. The paper initiates with an examination of the rationale behind the utilisation of PLS-SEM, subsequently offering a concise overview of the fundamental principles for the reporting of PLS-SEM outcomes. The paper also provides a brief overview of the basic concepts of sample size, assumptions, model predictive power, Importance-Performance Map (IPMA) and moderating in PLS-SEM.

1. INTRODUCTION

In many academic studies, covariance-based structural equation modeling (CB-SEM) for fitting and hypothesis testing of research models describing the relationships between latent variables has been carried out using LISREL and AMOS software as dominant. In recent years, the number of papers analysing SEM using the PLS-SEM approach has increased dramatically compared to CB-SEM (Hair et al., 2017a, b).

PLS-SEM has become a popular method that relaxes the assumption of multivariate normal distribution of data and does not require large sample sizes for complex models where mediation/ moderating effects can be easily investigated. Especially with the development of user-friendly software packages such as SmartPLS that require little technical knowledge to

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use, the use of structural equation modeling in data analysis has further increased. The aim of this study is to provide researchers with easy-to-understand and practical tips on how to report the results of partial least squares structural equation modeling (PLS-SEM) analysis. In the study, first, the question CB-SEM or PLS-SEM? Then, PLS-SEM model specifications and assumptions are discussed, and finally, the reporting of PLS-SEM results according to whether the indicators are reflective, or formative is tabulated.

2. CB-SEM or PLS-SEM

Jöreskog (1973) and Joreskog & Sorbom (1988) CB-SEM, usually conducted by software such as LISREL or AMOS, uses the covariance matrix for parameter estimation and estimates the model parameters considering only the common variance. In contrast, PLS-SEM performs variance-based estimation because it takes into account the total variance and uses the total variance to estimate the parameters (Hair et al., 2017a, b). Table 1 provides a detailed comparison of CB-SEM and PLS-SEM (Hair et al., 2011a; 2012; Hair et al., 2014;2016; Crisci, 2012, Yılmaz et al., 2024).

Table 1.
Comparison of CB-SEM and PLS-SEM methods

	CB-SEM	PLS-SEM
Aim	"Parameter-driven: Uses model parameters to explain covariance among indicators.	Identification-Prediction oriented: Uses latent variable scores to explain covariance among indicators.
Approach	Covariance based: The method aims to minimize error covariances to increase the accuracy of the parameters.	Variance-based: The method aims to explain the variance of latent variables.
Optimality	CB-SEM provides optimal parameter estimation when the hypotheses correctly explain the covariance of all indicators and all assumptions are met.	PLS-SEM provides accurate estimates with fewer assumptions.
Algorithm Compatibility	Full Information Method: It allows simultaneous estimation of parameters by minimizing the error between the observed and estimated covariance/correlation matrix.	Limited Information Method: A multi-stage iteration including the PLS method is used. Parameters are estimated with the help of the scores obtained through this iteration.
Clutch	It is used to test the theory.	It is used for estimating parameters and decision making.
Latent Variable Scores	The estimate is made by taking into account all the indicators.	Prediction is made using latent variable scores.
Measurement Model	Only the reflective measurement model is used.	Formative and reflective measurement model is used.
Measurement Errors	It combines variance and measurement errors into a single estimate.	It separates irrelevant variance from the structural part of the model.
Scale	Continuous, equally spaced, ordinal scale	Continuous, equally spaced and categorical
Distribution Assumptions	If it is estimated with ML, it has a multivariate normal distribution. It is a parametric method.	There is no assumption about the distribution. It is a non-parametric method.
Sample Size	Works with large volume samples (Number of units>200).	It can work with small volume samples (40<number of units<200).
Model Accuracy	The accuracy of the theoretical model depends on all indicators explaining the covariance correctly.	The accuracy of the theoretical model depends on the strength of the relationship between the latent variables".

Table 1. (continues)

	CB-SEM	PLS-SEM
Consistency of Estimators	"Given the accuracy of the model and the appropriateness of the assumptions, the parameter estimates are consistent.	"Bias may occur in parameter estimates. Biased parameter estimates occur when loadings are small, and path coefficients are large. However, bias decreases as the number of latent variables, sample size and indicators increase.
Complexity of the Model	It is problematic for large models containing 50 or more variables.	Suitable for large models.
Evaluation of the Model	The model is developed through hypothesis testing. H0 : $S - \hat{\Sigma} = 0$ Goodness of fit indices are used.	There is no specific goodness of fit index used in testing parameter estimates. Parameter estimates are interpreted according to Jacknife and Bootstrap methods.
Indicators per Structure	There must be at least 3-4 to meet the identification requirements.	Must be 1, 2 or more.
Statistical Tests for Parameter Indicators	Assumptions must be met.	Jackknifing or Bootstrapping is required for inference.
Software Used	Lisrel , Amos , MPLUS et al.	SmartPLS , PLSGraph , PLSGUI et al.
Applicability	The phenomena analyzed are clear. The model is not complex. It is based on reflective indicators. It usually has binding assumptions about distribution, multicollinearity, and sample size. multi-group hierarchical data. It compares models from different populations with a single objective function".	It is a new phenomenon. It is a relatively complex model due to the large number of latent variables and indicators. It can be modelled in different ways, including reflective and formative. There are no rules to follow regarding normality assumptions, independence, and sample size".

According to Table 1, one of the main differences between CB-SEM and PLS-SEM approaches is that PLS-SEM can work with non-normally distributed data because it is a non-parametric method. At the same time, PLS-SEM can work with much smaller sample sizes than CB-SEM. Because of these characteristics, PLS-SEM is preferred by researchers and is considered an appropriate approach to test the predictive model for the variables under study (Ringle et al., 2012, 2014).

Although it is stated in Table 1 that goodness-of-fit measures are not required for PLS-SEM, so far there is no standardised goodness-of-fit criterion for PLS-SEM. The SRMR value is considered instead of goodness-of-fit values such as Chi-square, RMSEA, GoF, NFI and the bootstrapping method, which is considered to give more reliable results than the traditional method (Henseler, et al., 2009, 2010, 2014).

PLS-SEM is used because PLS-SEM provides simpler methods for identifying regulatory and mediating relationships, and SmartPLS software provides these processes better. In research, the PLS-SEM approach is considered advantageous in producing more practical results. PLS-SEM is an appropriate approach for theory development and prediction, while CB-SEM is used to test and validate a theory (Hair et al., 2011a,b, 2012a,b). When using PLS-SEM and CB-SEM, researchers are most interested in comparing the differences in model predictions. It is important to note that both approaches are actually complementary, not that one approach is superior to the other (Henseler et al., 2014, 2016). The aim of this comparison is to highlight the differences between the two approaches and to guide the determination of the appropriate approach for research according to these differences.

3. BASIC FEATURES

3.1. Data Characteristics

The characteristics of the data are crucial in deciding whether to use PLS-SEM. In PLS-SEM, the assumptions regarding the size of the sample volume and the distribution of the data have a more flexible structure than in other methods.

3.2. Sample Size

PLS-SEM can certainly be used with smaller samples, but the nature of the population determines the situations in which small sample sizes are acceptable. Finally, Kock & Hadaya (2018) propose two new approaches to minimum sample size calculations: the inverse square root method and the gamma exponential method.

There are several factors to consider when determining sample size in PLS-SEM. References to these factors and methods of determination are given below:

- The complexity of the model, i.e. the number of indicator and latent variables, is an important factor in determining the sample size. In general, more complex models (more independent variables or more latent variables) require a larger sample size.
- In PLS-SEM, sample size is usually determined by a power analysis. In this analysis, factors such as effect size, significance level (usually 0.05) and power (usually 0.80) are determined using software such as G*power and Minitab.
- For each parameter in the research model (for each arrow), 10 observations are recommended. Experience shows that if there are 30 Likert statements in the questionnaire, the sample size can be 300.
- As a general guideline, sample sizes between 150 and 300 are generally considered adequate for PLS-SEM applications. However, this number may be higher depending on the complexity of the model and the effect size.

Kock & Hadaya (2016), at 5% significance level

$$n_{min} > \left(\frac{2.486}{|path\ coff._{min}|}\right)^2 \qquad (1)$$

For example, if we want the smallest path coefficient to be 0.20, the sample size should be at least 155.

3.3. Distributional Assumptions

Many authors state that the main reason for choosing PLS-SEM is the lack of distributional assumptions (Hair et al., 2012b). While this in itself is an advantage of using PLS-SEM in social science studies, which almost always rely on non-normal data (especially data collected through surveys), it is not a sufficient justification. When the size of the data set is limited, CB-SEM may produce anomalous results if the data are not multivariate normally distributed. In similar cases, PLS-SEM is more robust (Sarstedt et al., 2014,2017).

3.4. Model Specifications

Compared to multivariate regression or CB-SEM, PLS-SEM is not affected by small sample sizes, skewed distribution of the data set and multiple intercorrelation problems between variables. Therefore, PLS-SEM offers great convenience in model building. Because of these characteristics, it is referred to as a flexible modelling method. PLS-SEM consists of a structural model and a measurement model in which the relationship between observed variables and latent variables and the relationship between latent variables are analysed.

The reflective measurement model assumes that indicators reflect their latent variables. In other words, variability in the structures causes variability in the measures. *In the formative measurement model*, each indicator or subset of indicators represents a different dimension of the underlying concept. Therefore, unlike the reflective model, the formative model does not assume homogeneity and one-dimensionality of the block. The latent variable is defined as a linear combination of its indicators. Table 2 will help you to understand more clearly the characteristics of both models and the analysis processes. The reflective model represents the external reflections of structural variables, while the formative model is concerned with the indicators that form and shape the internal structures. Information about the criteria in the tables (2,3 and 4) are tabulated by summarizing the publications of Hair et al., Henseler et al., Ringle et al. and Sarstedt et al.

Table 2.
Basic information about the reflective and formative model

Feature	Reflective Measurement Model	Formative Measurement Model
Definition	"Indicators are reflections of structural variables and there is a causal relationship between variables.	The indicators constitute the structural variable and are independent of each other.
Relationship Type	Reflexive - Indicators are a result of the variable.	Formative - Indicators shape the variable.
Features	1. The indicators are highly correlated with each other. 2. Variables reflect an internal structure.	1. Indicators are independent and distinct. 2. Variables consist of external properties.
Indicator loads	The first step involves examining the indicator loadings. Loadings above 0.708 (0.7082 = 0.501) are recommended as they indicate that the construct explains more than 50 percent of the variance of the indicator and therefore provides acceptable item reliability.	
Measurement Model Evaluation	1. External Validity: Indicators must have high loadings. 2. Internal Validity: Factor loadings must be 0.7 and above.	1. External Validity: Each indicator must be meaningful as an independent item. 2.Internal Validity: Multicollinearity among indicators needs to be checked.
Relationship Between Indicators	High correlation is expected.	The indicators are independent and unrelated.
Weights	Indicators should have high weights (i.e. high factor loadings).	The weights of the indicators reflect the structuring effects.
Examples of Usage Areas	Situations such as psychological scales, attitudes, personality measurements.	External factors such as economic indicators and brand perception".

4. CRITERIA IN PLS-SEM TO EVALUATE MEASUREMENT AND STRUCTURAL MODEL WHEN INDICATORS ARE REFLECTIVE

The criteria used to evaluate the measurement and structural model in models with reflective indicators in PLS-SEM are given in Table 3.

Table 3.
Criteria used to assess the measurement and structural model when indicators are reflective

Model Type	Criterion	Description
Reflective Measurement Model	Indicator Reliability	"Assess if outer loadings of indicators are above a threshold *(usually > 0.708).* Indicators with low loadings may be removed. Loadings above 0.708 ($0.708^2 = 0.501$) are acceptable as the construct explains more than 50 percent of the variance of the indicator and is recommended as it indicates item reliability.
	Internal Consistency	Measured with Composite Reliability (CR). A value *of > 0.70* is generally considered acceptable.
	Convergent Validity	Assessed using Average Variance Extracted (AVE). A *value > 0.50* indicates adequate convergent validity.
	Discriminant Validity	Evaluated using the Fornell-Larcker Criterion (the square root of AVE should be greater than the correlation between constructs) and HTMT (Heterotrait-Monotrait ratio) which should be *below 0.85.* Henseler et al. (2015) suggest a threshold value of *0.90* for structural models with conceptually very similar structures.
	Multicollinearity	Measured by Variance Inflation Factor (VIF). *A VIF > 5* indicates potential multicollinearity issues.
Reflective Structural Model	R^2 (R-squared)	Measures the explanatory power of the model. Values *of 0.25 (weak), 0.50 (moderate), and 0.75 (strong)* are typical thresholds.
	Effect Size (f^2)	Indicates the effect of a predictor variable on an endogenous construct. Thresholds: *Small (0.02), Medium (0.15), (0.35). Large*
	Predictive Relevance (Q^2)	Assessed through blindfolding procedure. A *$Q^2 > 0$* indicates predictive relevance.
	Path Coefficients	Examine the significance and strength of the relationships between constructs (using bootstrapping).
	Model Fit	Though PLS does not directly provide fit indices like covariance-based SEM, you can use Standardized Root Mean Square Residual *(SRMR)<0.08* considered good.
Global Model Evaluation	GoF	This is an overall fit index used in PLS, calculated by combining the measurement and structural model fit. A *threshold of 0.36 is considered a good fit.*
Model comparison		Select the model that minimizes the value in BIC or GM compared to other models".

Table 4 presents the criteria used to evaluate the measurement and structural model when PLS-SEM' is formative to the indicators.

Table 4.
Criteria used in the evaluation of the measurement and structural model when indicators are formative

Model Type	Criterion	Explanation
Formative Measurement Model	Collinearity (VIF)	"Measured by Variance Inflation Factor (VIF). A VIF *value > 5* indicates multicollinearity issues among the indicators.
	Indicator weight Significance	Check the significance of the weights of the indicators to ensure they contribute meaningfully to the construct (using bootstrapping).
	Indicator Relevance	Evaluate whether the weights of the formative indicators are statistically significant. Indicators with insignificant weights should be reconsidered or removed.
	Content Validity	Ensure that the indicators used in the formative model cover all relevant dimensions of the construct. This is usually done through expert judgment.
	Nomological Validity	Test if the construct has a valid relationship with other constructs, typically through structural model assessment.
Formative Structural Model	R^2 (R-squared)	The explanatory power of the endogenous construct(s). It measures how much variance in the dependent construct is explained by the independent variables.
	Effect Size (f^2)	Evaluate the impact of predictor constructs on the endogenous construct. *Thresholds: Small (0.02), Medium (0.15), Large (0.35).*
	Predictive Relevance (Q^2)	Assessed through blindfolding procedure. A *Q^2 value > 0* indicates predictive relevance for the endogenous construct.
	Path Coefficients	Examine the significance and strength of relationships between constructs (using bootstrapping). Path coefficients for formative constructs should be interpreted cautiously.
Global Model Evaluation	Goodness of Fit (GoF)	A general index for the overall model fit. Though not directly a focus in formative models, it can still be used as a *global measure. A GoF above 0.36 is considered good.*
Model comparison		Select the model that minimizes the value in BIC or GM compared to other models".

5. PREDICTIVE POWER OF MODEL

For PLSpredict-based assessment of a model's predictive power, researchers can make use of several prediction statistics that measure the amount of prediction error MAE and RMSEA. It is that defined as the square root of the mean of the squared differences between the forecasts and the actual observations.

The following guidelines apply when comparing RMSE (or MAE) values with regression model (LM) values (Shmueli et al., 2016):

- "If the PLS-SEM analysis yields higher prediction errors in terms of RMSE (or MAE) for all indicators compared to the LM benchmark, this indicates that the model lacks predictive power.
- If the majority of the dependent structure indicators in the PLS-SEM analysis produce higher prediction errors compared to the LM benchmark, this indicates that the model has low predictive power.
- If a minority (or the same number) of indicators in the PLS-SEM analysis yield higher prediction errors compared to the pure LM benchmark, this indicates a moderate level of predictive power.

- If none of the indicators in the PLS-SEM analysis have higher RMSE (or MAE) values compared to the naive LM benchmark, the model has high predictive power".

6. IMPORTANCE-PERFORMANCE MAP ANALYSIS (IPMA)

It is a method used to analyse the importance and performance of certain features of a product or service as perceived by the customer. This tool, first developed by Martilla & James in 1977, helps businesses visualise which areas they should focus on to increase customer satisfaction and use resources more effectively. IPMA is a map that enables the evaluation of the characteristics of a particular product or service from the customer's perspective. This analysis method is used within the framework of partial least squares structural equation modelling (PLS-SEM) and is based on two main measures:

- Importance (X axis): Indicates the influence of a construct on a specific objective. This effect arises as a result of the direct or indirect relationships between the variables in the model. In other words, how valuable each feature is to customers.
- Performance (Y axis): It shows the current performance level of each construct, i.e. its relative success on the target construct. In other words, it is the perceived success of the product or service on these features.

The IPMA analysis combines these two dimensions and graphically shows both how important the constructs are and how they are currently performing. This analysis is frequently used in areas such as marketing, service quality, customer experience and business management, particularly to develop strategies to improve customer satisfaction. Each attribute is placed on an evaluation scale and shown on a specific coordinate. The resulting map is divided into four main regions, providing guidance on how the attributes should be strategically managed.

It is used to analyse the importance and levels of antecedents (exogenous latent variable) that affect the formation of any service (endogenous latent variable) as perceived by individuals. Basically, IPMA visualises which areas people should focus on in order to increase their satisfaction and use resources more effectively in the organisation. IPMA is used in the context of PLS-SEM and is based on two main measures: Importance (X-axis): shows the effect of exogenous latent variables on a specific target construct, the endogenous latent variable. This effect arises because of direct or indirect relationships between the variables in the model. Performance (Y-axis): It shows the relative performance of each exogenous latent variable on the target endogenous latent variable under consideration. By combining importance and performance, IPMA graphically shows both the importance and the performance of latent variables. As shown in Figure 1, the map is divided into 4 regions.

Q1- Strong areas to be maintained (high importance, high performance), *Q2- Areas to be improved (high importance, low performance)*: This area includes characteristics that are of high importance for individuals but low in terms of performance. Therefore, these are the areas that need to be improved as a priority. *Q3-Areas where over-investment should be avoided (low importance, high performance):* A decrease in performance in these features will not affect the level of importance given to the target structure. *Q4- Areas of secondary importance (low importance, low performance):* Includes features with both low importance and low performance (Sarstedt et al., 2024).

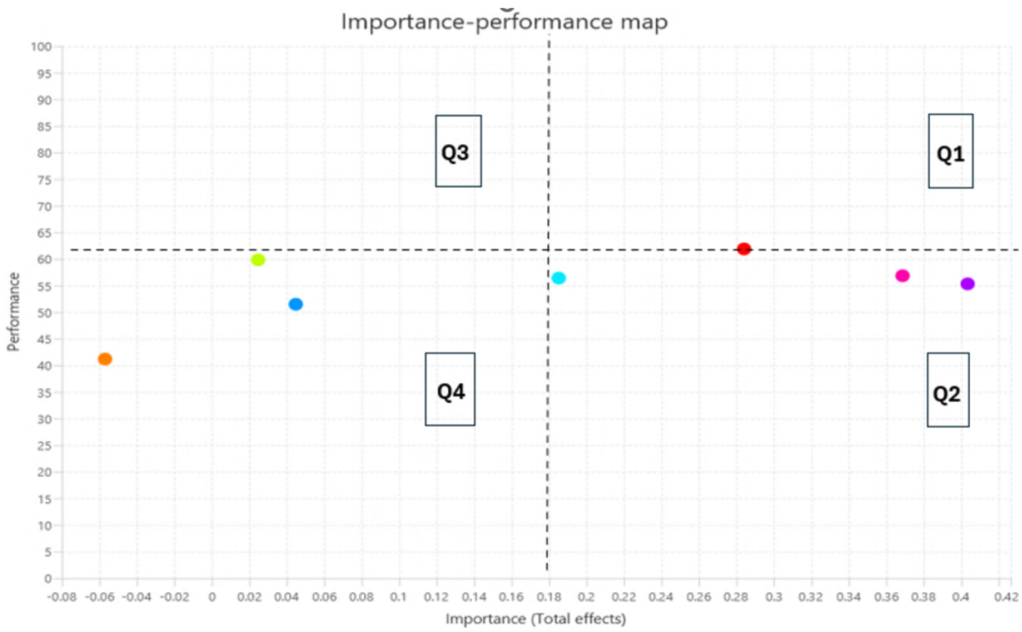

Figure 1. Importance-Performance Map Analysis, IPMA

7. MODERATING EFFECT

The structure that changes the effect of the exogenous (independent) latent variable on the endogenous (dependent) latent variable in an increasing or decreasing direction is called a 'moderating variable'. This moderating variable actually has a strong conditional effect on the relationship between the exogenous and endogenous latent variables.

For example, 'job opportunities' can change the expected relationship between the exogenous latent variable 'job dissatisfaction' and the endogenous latent variable 'turnover'. This is because if someone is dissatisfied with their job, they will consider moving to another job. Therefore, job opportunities can be a moderating variable. The hypothesis for the moderating effect is given below.

H1: Job opportunities moderates the effect of job dissatisfaction on turnover. When there is a high level of job opportunities in the work environment, job opportunities will positively increase the effect of job dissatisfaction on turnover.

Exogenous variable x Moderating variable→Endogenous variable

It is in the form for example, if the exogenous variable is denoted by *A*, the moderating variable by *M* and the endogenous variable by *Y*, the reporting of the result can be written as Table 5.

Table 5.
Hypothesis Test Reporting of The Result

Hypothesis	Coefficient of effect	t-value	p-value	Decision
AxM→Y	0.38***	4.89	P<0.01	Supported

***p<0.01

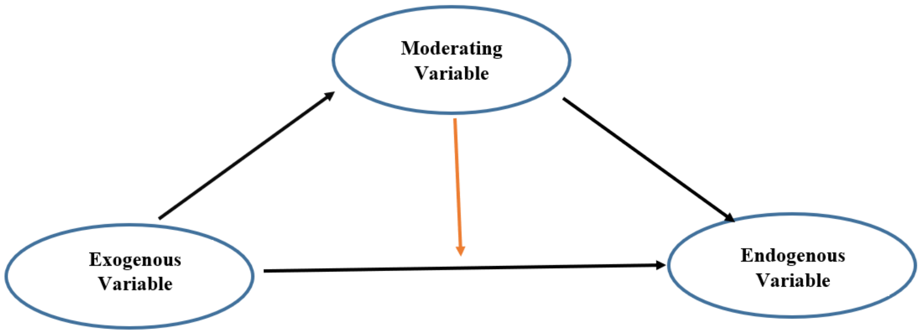

Figure 2. Moderating effect

8. CONCLUSION

The aim of this paper is to give practical tips to researchers by briefly explaining how to handle PLS-SEM results. PLS-SEM is increasingly being applied to predict SEM (Hair et al., 2013, 2014, 2018, 2019). Before submitting their papers to journals, authors may need a comprehensive but brief and practical overview to ensure that PLS-SEM results are analysed and reported correctly. Many previous studies have addressed these issues (Hair et al., 2011; Hair et al., 2013; Hair et al., 2012b; Henseler et al., 2009). In recent years, new theoretical developments and easy-to-implement analyses in software have been developed and updated for PLS-SEM. For this reason, the results presented in this study should not be regarded as ultimately correct and unchangeable.

This study may be helpful for researchers who have never used PLS-SEM or who are new to PLS-SEM in designing and writing their studies. The information presented in the study may also be important for academics and journal editors who will review articles written on this subject. Although there are many reasons for using PLS-SEM, some of these reasons are briefly summarised below.

- The measurement model and the structural model can be analysed simultaneously and simultaneously,
- Since it is a variance-based approach, it does not require large samples,
- Provides more accurate estimates of the significance of direct and indirect effects.
- Practical for analysing models with hierarchical and moderating/mediating effects.
- When the research objective is to better understand increasing complexity by exploring, extensions of accepted theoretical models,
- PLS-SEM can give reliable results even if the sample size is smaller than 250. However, it is recommended not to be less than 150 units for academic manuscript.

The most important software that PLS-SEM analyses are commonly performed is SmartPLS. SmartPLS was developed by Ringle et al. (2005) and the software has been updated and made available to researchers until today. The software has a user interface that is easy to learn and use. Since the software uses Bootstrap (a resampling method for statistical inference) in the parameter estimation and hypothesis testing process, the significance of the coefficients does not change even if the coefficients calculated at different times are estimated differently.

PLS-SEM is a useful method in making reliable analyses by allowing direct and indirect effects as well as mediating and moderating latent variables to be included in the model. When the analyses in PLS-SEM are performed in the correct order and reported in the desired standards, it increases the scientific of the academic study. Researchers should follow the guidelines given in the tables by reporting the basic criteria for measurement and structural models in the order and standards mentioned in this study.

The present study provides a concise overview of the reporting of PLS-SEM results, omitting detailed discussions on topics such as mediation and moderation, which will be the focus of a future study. Additionally, the execution of PLS-SEM analyses in SmartPLS software and the interpretation of results remain unaddressed. For a comprehensive exploration of these subjects, reference is recommended to the book by Yılmaz et al., (2024).

REFERENCES

Crisci, A., (2012). Estimation methods for the structural equation models: Maximum likelihood, partial least squares E-generalized maximum entropy. Journal of Applied Quantitative Methods, 7(2), 3-17.

Hair, J. F., Henseler, J., Dijkstra, T. K., & Sarstedt, M. (2014). Common beliefs and reality about partial least squares: Comments on Rönkkö and Evermann. Organizational Research Methods, 17(2), 182–209.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011a). PLS-SEM: Indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139–151. https://doi.org./10.2753/MTP1069-6679190202

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017a), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), Sage, Thousand Oaks, CA.

Hair, J. F., Hult, G. T. M., Ringle, C.M., Sarstedt, M., & Thiele, K. O. (2017b). Mirror, Mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods, Journal of the Academy of Marketing Science, 45(5), 616-632. https://doi.org/10.1007/s11747-017-0517-x

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: indeed, a silver bullet, Journal of Marketing Theory and Practice, 19(2), 139-151. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: rigorous applications, better results and higher acceptance, Long Range Planning, 46(1-2), 1-12. https://doi.org/10.1016/j.lrp.2013.01.001

Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): an emerging tool in business research, European Business Review, 26(2), 106-121. https://doi.org/10.1108/EBR-10-2013-0128

Hair, J. F., Sarstedt, M., Matthews, L., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: part I – method, European Business Review, 28(1), 63-76. https://doi.org/10.1108/EBR-09-2015-0094

Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012a). The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications, Long Range Planning, 45(5-6), 320-340. https://doi.org/10.1016/j.lrp.2012.09.008

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2018). Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM), Sage, Thousand Oaks, CA.

Hair, J. F., Sarstedt, M., Ringle, C. M. & Mena, J. A. (2012) An assessment of the use of partial least squares structural equation modeling in marketing research. Journal of the Academy of Marketing Science, 40, 414-433. https://doi.org/10.1007/s11747-011-0261-6

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM, European Business Review, 31(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares, European Journal of Marketing, 53(4), 566-584. https://doi.org/10.1108/EJM-10-2018-0665

Henseler, J., & Fassott, G. (2010). Testing moderating effects in PLS path models: an illustration of available procedures, in Esposito Vinzi, V., Chin, WW, Henseler, J., et al. (Eds), Handbook of Partial Least Squares (pp. 713-735). Berlin, Heidelberg: Springer.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., Ketchen, D. J., Hair, J. F., Hult, G. T. M., & Calantone, R. J. (2014) Common Beliefs and Reality about Partial Least Squares: Comments on Ronkko & Evermann (2013). Organizational Research Methods, 17, 182-209. https://doi.org/10.1177/1094428114526928

Henseler, J., Hubona, G.S., & Ray, P.A. (2016). Using PLS path modeling in new technology research: Updated guidelines, Industrial Management and Data Systems, 116(1), 1-19.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing, in Sinkovics, R.R. and Ghauri, P.N. (Eds), New Challenges to International Marketing, Emerald Group Publishing, 20, 277-319. https://doi.org/10.1108/S1474-7979(2009) 0000020014

Joreskog, K. G. (1973). Analysis of covariance structures. In P. R. Krishnaiah (Ed.), Multivariate Analysis-III ed. (pp. 263-285). New York: Academic Press.

Joreskog, K. G., & Sorbom D. (1988). PRELIS: A Program for Multivariate Data Screening and Data Summarization. A Preprocessor for LISREL. Chicago: SSI, Inc.

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The Inverse Square Root and Gamma-Exponential Methods. Information Systems Journal, 28, 227-261.

Martilla, J. A., & James, J. C. (1977). Importance-performance analysis. Journal of Marketing, 41(1), 77–79. https://doi.org/10.2307/1250495

Ringle, C. M., Sarstedt, M., & Straub, D. W. (2012). Editor's comments: A critical look at the use of PLS-SEM in "MIS Quarterly.", MIS Quarterly, 36(1), iii–xiv. https://doi.org/10.2307/41410402

Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies! Journal of Business Research, 69(10), 3998–4010. https://doi.org/10.1016/j.jbusres.2016.06.007

Sarstedt, M., Richter, N. F., Hauff, S., & Ringle, C.M. (2024). Combined importance–performance map analysis (cIPMA) in partial least squares structural equation modeling (PLS–SEM): a SmartPLS 4 tutorial. Journal of Marketing Analytics, 12, 746–760. https://doi.org/10.1057/s41270-024-00325-y

Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. Journal of Family Business Strategy, 5(1), 105–115. https://doi.org/10.1016/j.jfbs.2014.01.002

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: evaluating the predictive performance of PLS models. Journal of Business Research, 69(10), 4552–4564. https://doi.org/10.1016/j.jbusres.2016.03.049

Yılmaz, V., Kinaş, Y., & Olgaç S. (2024). Smart-Pls 4 ile Yapısal Eşitlik Modellemesi, Detay Yayıncılık, Ankara.

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