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PLS-SEM for Multivariate Analysis: A Practical Guide to Educational Research using SmartPLS

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Abstract

Implementation of PLS-SEM in educational research has developed significantly, but there are variations in the presentation of the analysis results. This study aims to provide practical understanding to researchers who intend to utilize PLS-SEM in multivariate analysis to enhance the recognition and validity of the resultant research outcomes using SmartPLS. This research is a literature study that conducts content analysis of relevant books and publications. The research results present PLS-SEM analysis using SmartPLS on reflective and formative research models with first-order and second-order approaches through measurement model evaluation (outer model) and structural model evaluation (inner model) with various criteria. Evaluation of the reflective measurement model consists of reflective indicator loadings, internal consistency reliability, convergent validity, and discriminant validity. The review of the formative measurement model consists of convergent validity, collinearity, and statistical significance of weights. The structural model evaluation consists of the collinearity test, significance value, f square, R square, Q square, SRMR, PLSpredict, and robustness checks. Therefore, this study can provide guidance using SmartPLS in conducting PLS-SEM analysis and presenting acceptable analysis results

Keywords: PLS-SEM, smartPLS, partial least squares, Structural equation modelling, multivariate analysis.

1. Introduction

Statistical analysis has been an essential tool for educational science scholars. At first, researchers relied on analyzing one or two variables to understand data and the connections between them. Understanding the complex connections in current educational research requires advanced multivariate data analysis techniques. Multivariate analysis involves the application of statistical methods that simultaneously evaluate many variables, typically representing measures associated with individuals, corporations, events, processes, situations, and other things. The acquisition of these metrics often occurs through surveys or observations, which serve as primary data sources. However, they can also be from secondary databases (Hair et al., 2017).

Multivariate data analysis encompasses several statistical procedures, with a particular emphasis on regression-based analytic techniques (Grech & Calleja, 2018). Nevertheless, these analytical procedures have constraints when formulating a basic model structure. They necessitate that all variables can be observed and assume that all variables are measured accurately (Berman, 1971; Groenwold & Dekkers, 2023; Haenlein & Kaplan, 2004; Poon & Tang, 2002). As a result, researchers are utilizing structural modelling approaches (SEM), which enable the simultaneous modelling and estimation of intricate interactions among various dependent and independent variables. SEM combines statistical methods, such as factor analysis, regression analysis, and path analysis, to test the relationship between observed and latent variables in a single framework. SEM can investigate the complex relationship between an observed variable (which can be measured directly) and a latent variable. This method uses a measurement model (to examine the relationship between a latency variable and the observed indicator) and structural models (to test the relation between the latent variables). Researchers can test and develop more complex theoretical models through SEM by testing simultaneous relationships between existing variables. It allows for exploring the direct and indirect influences between the latent variables (Kwok et al., 2018; Sarstedt & Ringle, 2020).

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The two primary methods that dominate structural equation modelling (SEM) are covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). CB-SEM is employed to corroborate or refute the underlying theory and hypothesis, whereas PLS-SEM primarily concentrates on revealing the variability in the model's dependent variable (Dash & Paul, 2021). CB-SEM gained popularity primarily due to its capability to evaluate hypotheses formulated within a confirmatory model. Nevertheless, the inflexibility of CB-SEM, particularly in dealing with instances of non-normal data and complex models, gave rise to the development of PLS-SEM. PLS-SEM has evolved as a more flexible option to manage non-normal scenarios and assess formative and reflective research models, which CB-SEM cannot do (Hair et al., 2020).

Despite the flexibility offered by PLS-SEM, several research studies utilizing this method demonstrate variations in the assessment of structures and the quality of structural models (Bayonne et al., 2020; Zeng et al., 2021). In order to address these disparities and enhance the accuracy of study findings, it is imperative to establish explicit criteria for the standardized presentation of research reports utilizing PLS-SEM. This study aims to provide practical understanding to researchers who intend to utilize PLS-SEM in multivariate analysis to enhance the recognition and validity of the resultant research outcomes using SmartPLS software. This study provides a thorough and detailed examination of the principles, practical uses, and theoretical comprehension of PLS-SEM for multivariate analysis, thereby offering a noteworthy addition to scientific research in the field of multivariate analysis.

2. Research Methods

This study is a library study that utilizes information from many library sources, including books, literature, and documents on the subject under examination. This data-gathering method explicitly targets the comprehension and examination of information in scientific literature pertinent to study subjects (Elo et al., 2014; George, 2008). Within PLS-SEM research, the library's examination will entail conducting thorough searches and gathering material that comprehensively evaluates PLS-SEM and its implementations in multivariate analysis. This procedure allows researchers to investigate PLS-SEM's theory and fundamental principles and analyze approaches used in prior research. Data analysis involves employing a content analysis strategy, which employs a set of methodologies to evaluate and draw conclusions from books or other relevant publications. Content analysis is a method to extract relevant information from scientific publications (Slocum & Rolf, 2021). It involves identifying patterns, significant findings, and key concepts related to PLS-SEM in multivariate analysis within the social sciences.

3. Results and Discussion

3.1 Understanding of SEM analysis

SEM is a multivariate statistical analysis technique used to analyze the structural relationships between measured variables and latent constructions. SEM includes confirmation factor analysis to assess measurement models, path analysis to evaluate structural models, and enables estimation of relations between latent variables after considering measurement errors. SEM provides a framework for testing the hypothesis of the relationship between observed variables and latent variables, which allows researchers to test complex models with multiple paths and inter-variable correlations. SEM is based on two fundamental concepts: latent variables and measurement models. Latent variables are unobserved constructs that are not directly measurable but are inferred from observed variables. Latent variables are represented in SEM as ovals or circles. Measurement models specify the relationships between latent variables and their observable indicators. These models describe how the observed variables measure the latent variable. Measurement models are represented in SEM as rectangles or squares (Hair et al., 2017).

SEM tests theoretical models for exploration and confirmation purposes, accommodating reflective and formative constructions. SEM also accommodates complex model structures, such as mediation moderation, and allows for model-matching assessments. There are two approaches in SEM analysis: CB-SEM and PLS-SEM. CB-SEM focuses on testing and confirming the theory, which requires a large sample size and data normality. CB-SEM estimates model parameters by minimizing the difference between the model's observed and implied covariance matrix. PLS-SEM is used for theoretical development, allowing small samples and formative measurements. PLS-SEM maximizes the described variance of the dependent construction and does not impose strict data requirements (Hair et al., 2018).

3.2 Reasons for Using PLS-SEM

PLS-SEM is a statistical method that estimates partial model structures by combining principal components analysis with ordinary least squares regressions. In this context, the researcher must explain the fundamental reasons for using PLS-SEM analysis in the research methodology.

1. Research Design.

The researcher describes the type of research and approach used according to research objectives. Researchers ensure that the research objectives are relevant for using PLS-SEM analysis. PLS-SEM is variance-based, accounting for a total variance to estimate parameters, and is suitable for exploratory research, mainly when the research goal is prediction and theory development (Hair et al., 2017).

2. Population and sample.

The research population and sample should involve identifying the target population from which data will be collected and selecting a representative part of that population as the research sample. It is essential to clearly define the population of interest based on the research objectives and scope of the study. The sample must represent the population to ensure that the findings can be generalized back to the population. The size and characteristics of the sample are critical to the validity and generalizability of the research results (Creswell, 2013; Creswell & Creswell, 2018; Djamba & Neuman, 2014; Tuckman & Harper, 2012). PLS-SEM can be used for small sample sizes but is also suitable for large ones. It depends on the complexity of the model and the number of indicators and constructs being analyzed. A good sample size in PLS-SEM should be determined based on the specific characteristics of the model, the nature of the research objectives, and the statistical power required to obtain reliable and valid results. Researchers should consider these factors carefully and conduct appropriate analysis to ensure that the sample size is adequate for PLS-SEM analysis. Small samples tend to result in the assumption of data normality distribution not being met, but PLS-SEM can overcome this through bias-corrected and accelerated (BCa) bootstrapping routines (Hair et al., 2019). Hair et al. (2021) explain that there is no identification issue when using a small sample, but the larger sample size will increase the precision and consistency of the PLS-SEM estimate. Kock and Hadaya (2018) suggest using the gamma exponential and inverse square root methods to get the minimum sample size. If a statistical test strength of 80% with levels of minimum path coefficients 0.41-0.5 and significant levels of 1%, 5%, and 10%, the minimum sample size in PLS-SEM is 41, 24, and 19, respectively. The same thing if a statistical test strength of 80% with levels of minimum path coefficients 0.21-0.3 and significant levels of 1%, 5%, and 10%; the minimum sample size in PLS-SEM is 251, 155, and 113, respectively (Hair et al., 2021). In addition to explaining the population, sample, and sample size, researchers must also convey the techniques used for data collection clearly and precisely to obtain samples that are in accordance with the research objectives. Table 1 shows the minimum sample size requirement for different significance levels and varying ranges of p_{min}.

Table 1. Minimum sample sizes for PLS-SEM

Path Coefficients (p_{min})	Significance level		
	1%	5%	10%
0.05 - 0.1	1004	619	451
0.11 - 0.2	251	155	113
0.21 - 0.3	112	69	51
0.31 - 0.4	63	39	29
0.41 - 0.5	41	25	19

Source: Hair et al. (2021:18)

3. Research Variables.

Researchers identify research variables, operational definitions of research variables used, and describe the constellation of research variables that demonstrate complex research models (Hair et al., 2018). PLS-SEM can measure complex research models to test the relationship between several independent, dependent, mediating, or moderator variables to analyze higher constructs with first-order or second-order analysis through a reflective or formative model approach. It is important to note that the choice between reflective and formative measurement models depends on the theoretical understanding of the measured construct (Hair et al., 2019). The choice of measurement model has implications for the interpretation of the results and the validity of the measurement model. Therefore, researchers should carefully consider the theoretical underpinnings of their constructs before deciding on the measurement model to use. A reflective measurement model assumes the construct itself causes the indicators of a latent construct. The indicators are expected to be highly correlated with the construct they measure. A formative measurement model assumes that the indicators of a latent construct form the construct itself. The indicators are anticipated to exhibit lower levels of correlation with each other and the construct they intend to test.

4. Research data sources.

Researchers write research data sources that will explain the research instruments and measurement scales used. In PLS-SEM analysis, primary and secondary data sources are two types of data that can be used to operationalize the constructs in the model. It is important to note that the choice between primary and secondary data sources depends on the research objectives and data availability (Hair et al., 2021). Primary data refers to data specially gathered for the current study endeavor. Data can be collected through various techniques such as surveys, interviews, experiments, or observations. Secondary data, in contrast, refers to data gathered for a purpose apart from the current research endeavor. The data can be sourced from several sources, such as company databases, social media platforms, customer tracking systems, national statistical bureaus, or publically accessible survey data.

5. Instrument Testing

In several cases in PLS-SEM analysis that use primary data, an instrument test is first conducted before being distributed to research respondents. Instrument testing is carried out to ensure that the instruments used in research are of good quality and reliable for measuring research variables. The validity test is through content and item validity tests (Aiken, 1985; Gregory, 2015; Lawshe, 1975). If the test results show that the research instrument is consistent and accurate in measuring the research variables, the research instrument can be distributed to respondents who are the research sample to obtain research data.

6. Data Analysis Methods.

The data analysis method provides descriptive analysis and PLS-SEM multivariate analysis. In this context, the researcher describes the characteristics and demographics of the research sample. Various descriptive statistical measures can also be displayed to get an overview of respondents' perceptions. In multivariate analysis, researchers use software to explain PLS-SEM analysis through measurement model evaluation and structural model evaluation. Several software tools can be used to assist PLS-SEM analysis, such as PLS-Graph (Chin, 2003), SmartPLS (Ringle et al., 2015; Ringle et al., 2005), Warp PLS, and the PLS-PM package in R (Hair et al., 2021). Among these software tools, SmartPLS is more accessible and generally requires little technical knowledge of the PLS-SEM method. Therefore, SmartPLS is the most widely used tool by researchers to help conduct PLS-SEM analysis. This article provides practical guidance for researchers conducting PLS-SEM analysis using SmartPLS.

3.3. Evaluation of PLS-SEM analysis with SmartPLS

Researchers prepare research data in the Excel application, which is stored in CSV format. Researchers also need to check outliner data because it can affect the results of PLS-SEM analysis. An outlier is an extreme response to a particular question or an extreme reaction to all questions (Hair et al., 2017). Several methods can be used to examine outlier data: the Mahalanobis Distance Statistic, box plot, and scatter plot graph. In addition, the prepared data can override the normality distribution with a small sample size. However, it should be noted that the sample size should be representative, considering the specific characteristics of the model, the nature of the research objectives, and the statistical power required to obtain reliable and valid results (Hair et al., 2018).

The first stage in PLS-SEM analysis is to formulate a conceptual model. It involves identifying latent and measured variables and determining the relationships between variables. Then, develop a measurement model that creates and links indicators (measured variables) with latent variables in SmartPLS software. Modeling refers to a recursive model where all causal effects are one-way based on research hypotheses. Latent variables are represented in SEM as ovals or circles, and measurement models are represented in SEM as rectangles or squares. The measurement model analyzes the relationship between the indicator and the latent variable, measuring how far the indicator can explain the latent variable. The relationship between indicators and their variables can be reflective or formative. Furthermore, the researcher drew the research model and imported the research data into the SmartPLS software (Sarstedt & Cheah, 2019).

3.3.1 Measurement Model

Measurement model evaluation is the first step in PLS-SEM analysis to ensure the validity and reliability of research constructs. In this stage, there are two approaches, reflective and formative measurement models, each with different measurement criteria. SmartPLS compiled a measurement model or an outer model of research involving several latent variables presented in the form of ovals or circles. Then, each indicator described as a rectangle or square is connected to a latent variable according to the research model. Such relationships can be reflective models where the direction of the arrow is from the variable latent to the indicator and formative models where it is from an indicator to a variable latency (Hair et al., 2017). After that, do "Calculate" and select "PLS Algorithm" on SmartPLS. This process will produce values of some criteria that should be submitted to the research report.

1. Reflective Model

First, reflective indicator loading is done by evaluating the outer loading value. Outer loading refers to the single regression coefficient between the indicator or measurement variable and the latent variable or constructs estimated in the model. It measures the strength of the relationship between the observed variables (indicators) and the unobserved constructs (latent variables) they represent. Outer loading is essential in assessing indicator quality, showing how well each indicator represents the latent variable it measures. An established rule of thumb is that a latent variable should explain a substantial part of each indicator's variance, usually at least 50%. It also implies that the variance shared between the construct and its indicator is larger than the measurement error variance. An indicator's outer loading should be above 0.708 since that number squared (0.7082) equals 0.50. In most instances, 0.70 is considered close enough to 0.708 to be acceptable (Hair et al., 2019). In SmartPLS, the outer loading value can be seen in "Outer loading" in "Final result." If the outer loading value is green, it follows the provisions, but if it is red, it indicates a lower outer loading value of 0.7, so the indicator must be removed from the latent variable. After that, calculate like the first method through the "PLS Algorithm" until the outer loading value is obtained in green or meets the specified value. However, it should be considered that the elimination of outer loading that does not meet the criteria is carried out as long as it increases the composite reliability value or average variance extracted (Hair et al., 2017).

Second, internal consistency reliability is measured from the value of Dillon-Goldstein's rho, or composite reliability (CR). In addition to CR, Cronbach's alpha (CA) is a value of internal consistency reliability that assumes equal indicator loadings that can be used to measure construct reliability. However, CR is considered better than CA because the CR measure considers the variance of the sum of variables in the block of interest. As a rule of thumb, a block is considered unidimensional when the CR is larger than 0.7 (Hair et al., 2017). The CR value of SmartPLS is shown in "Construct Reliability and Validity" in Quality criteria." If the CR value is green, then internal consistency reliability is acceptable.

Third, convergent validity measures the extent to which different dimensions of the same structure are positively related. Convergent validity assesses whether several indicators that measure the same base structure merge or have a high variance ratio. The standard measure to establish convergent validity on the construct level is average variance extracted (AVE), defined as the average value of the squared load of the indicator related to the construct, that is, the sum of squared loads divided by the number of indicators. AVE is equivalent to the commonality of a construct. AVE value of 0.50 or higher indicates that, on average, the construct explains more than half of the variance of its indicators. AVE of less than 0.50 indicates that, on average, more error remains in the items than the variance explained by the construct (Hair et al., 2019). The higher the AVE value, the better a latent variable or construct explains the variance of its indicators. The AVE value in SmartPLS is presented in "Construct Reliability and Validity" in Quality criteria." If the AVE value is green, then convergent validity is met.

Fourth, discriminant validity assesses the extent to which the measures of the constructs differ. This validity tests whether indicators of one construct are not closely related to indicators of other constructs. Several criteria, such as Cross-Loading, Fornel-Larcker, and Heterotrait-Monotrait Ratio (HTMT), can be used. Cross-loading is an approach by comparing the outer loading value of an indicator against its latent variable and the outer loading value of the indicator against other latent variables. The outer loading value of an indicator against its latent variable must be greater than the outer loading value of the indicator against other latent variables. It indicates that an indicator has proven to be better at measuring its latent variable than other variables. At the same time, the Fornel-Larcker criterion is an approach that compares the AVE square root of a latent variable to the correlation between that latent variable and other latent variables.

The square root value of a latent variable must be greater than the correlation value between that latent variable and other latent variables. The last approach is HTMT, which is the ratio of heterotraite correlation (between indicators of different constructs) compared to monotraite correlation (between indicators of the same construct) (Hair et al., 2017). The expected value on HTMT is less than 0.90, indicating that the correlation between indicators of different constructs is lower than the correlation between indicators of the same construct. Of the three discriminant evaluation approaches, Henseler et al. (2015) recommend using the HTMT approach due to its better ability to assess the validity of inter-construct discrimination in measurement models, provide more consistent results, and are more empirically reliable in discriminant validity analysis. The HTMT value can be seen in the "Discriminant Validity" in "Quality Criteria." HTMT values lower than 0.90 will be green so that it can be interpreted that the research instrument has good discriminant validity (see, for example, Subhaktiyasa et al., 2024).

2. Formative Model

In formative models, measurement evaluation uses criteria different from those of reflective models. The criteria to consider are convergent validity, the statistical significance and relevance of the indicator weights, and indicator collinearity (Hair et al., 2017). The first criterion, convergent validity in formative models, is determined through redundancy analysis. Researchers need to include alternative reflective indicators of formative measured constructs in questionnaires. Measuring one reflective item that describes the formative latent variable is sufficient (Cheah et al., 2019). How to perform such analysis on SmartPLS begins by describing a construct model of a latent variable with several formative items and relating them to the same latent variable but with one reflective item. Then, calculate the “PLS Algorithm” to culminate a correlation value or path coefficient on the constructed model. Convergent validity in formative models is accepted if the correlation of constructs measured formatively with the constructs of a single item reaches 0.70 or higher (Hair et al., 2017).

The second criterion is the assessment of indicator weights' statistical significance and relevance. In SmarPLS, the analysis process is performed by bootstrap calculations with subsamples 5000 times, and the BCa bootstrap confidence intervals method is chosen (Hair et al., 2017). Researchers need to pay attention to bootstrapping results on outer weight, where if the results show a significant value with a p-value smaller than 0.05, indicating a measurement item can explain the latent variable. However, if the result is insignificant (p-value greater than 0.05), then the measurement item of the latent variability does not need to be omitted if the loading factor value is greater than 0.50 (Hair et al., 2019). If the outer weight and outer loading are insignificant, then the indicator should be removed from the model, as there is no empirical support to retain it. Assessing the weak and robust relationship can refer to the outer weight value (original sample), where an outer weight close to 0 indicates a weak relationship and an outer weight close to +1 or -1 indicates a strong positive or negative relationship (Hair et al., 2019). The bootstrap results also show the value of the Variance Inflation Factor (VIF) as an indicator of collinearity evaluation for testing the third criterion. The higher the VIF value, the greater the level of collinearity between predictor constructs. Therefore, Hair et al. (2019) recommend a VIF value lower than 3 to indicate no multicollinearity. A collinearity problem may exist when the VIF value is three or greater and below 5.

3. Second Order Measurement Model

The second-order measurement model in PLS-SEM provides a framework for capturing constructs' complexity and multifaceted nature by simultaneously allowing researchers to examine the overall construct and its specific dimensions. This approach is precious when dealing with constructs that exhibit hierarchical relationships. By utilizing a second-order measurement model, researchers can represent the abstract nature of the construct and its specific subdimensions, providing a more detailed and nuanced representation of the construct under study. This approach allows researchers to gain insight into multifaceted constructs by considering the overall construct and its specific subdimensions, leading to a more comprehensive understanding of the investigated phenomenon. Moreover, the second-order measurement model is particularly beneficial when a more comprehensive understanding of the construct is required. By incorporating the overall construct and its specific dimensions, researchers can better understand the construct and its underlying relationships with other constructs in the model. This approach can lead to more accurate and robust results as it captures the complexity and multifaceted nature of the construct under study (Sarstedt et al., 2019).

Several approaches have been proposed for specifying and estimating higher-order constructs in PLS-SEM, with the most prominent ones being the (extended) repeated indicators approach and the two-stage approach (Ringle et al., 2012). When deciding which approach to use in second-order analysis, researchers should consider the specific characteristics of their higher-order constructs, the underlying relationships between the constructs, and the overall research objectives. Additionally, the choice of approach should be guided by the need to minimize biases in the estimation of the measurement and structural model relationships within the context of the study. The two-stage approach involves estimating the higher-order construct in two stages, focusing on minimizing biases in the structural model relationships. This approach demonstrates better parameter recovery of paths from exogenous constructs to the higher-order construct and from the higher-order construct to an endogenous construct in the path model. The rationale for this approach is its ability to provide a more valid estimation of the structural model relationships and accommodate reflective-formative and formative-formative type higher-order constructs (Sarstedt et al., 2019). The two-stage approach consists of the Embedded Two-Stage Approach (Ringle et al., 2012) and the Disjoint Two-Stage Approach (Becker et al., 2012). The embedded Two-Stage Approach estimates the measurement and structural models in a single step, making it more efficient and flexible. It is advantageous due to its efficiency, flexibility, robustness, and validity. The Disjoint Two-Stage Approach estimates the measurement and structural models in two separate steps. It is less efficient than the embedded two-stage approach but provides an alternative for analyzing second-order measurement models. However, it should be noted that these two approaches produce comparable results (Cheah et al., 2019).

This article provides a practical guide to measuring second-order models with an Embedded Two-Stage approach using SmartPLS. The first step is the same as the process in the measurement model. Researchers describe the research model on SmartPLS as consisting of latent variables (higher-order component), dimensions (lower-order component), and indicators of each dimension of research variables. These higher-order constructs are then linked according to the purpose of the study, and the relationship can be in the form of reflective-reflective, reflective-formative, formative-reflective, and formative-formative models (see, for example, Subhaktiyasa et al., 2023). Researchers do repeated indicators by inputting indicators according to their dimensions and all indicators on the latent variable.

After that, carry out the PLS Algorithm calculation process on SmartPLS. At this stage, researchers only focus on evaluating the measurement model at the dimension level, and the examination is adjusted to the criteria according to the reflective or formative model. In the reflective model, the initial check at the dimension level is the outer loading value of 0.708 or more. If the outer loading value does not meet the requirements, remove the indicator on the dimension (lower-order component) and latent variable (higher-order component) simultaneously and re-calculate the PLS Algorithm. If all outer loading values have been fulfilled, then the examination continues on the CR, AVE, and HTMT values according to the evaluation process of the reflective measurement model (Hair et al., 2019). The same thing is also applied to the formative measurement model evaluation model. If all criteria have been met, create a latent variable score, an indicator of the research variable. Continue with the same procedure, redraw the research model in SmartPLS, then input the latent variable score on each research variable and connect each variable according to the research objectives. Calculate the PLS Algorithm and evaluate at the variable level with the same procedure for assessing the measurement of reflective and formative models. If all criteria have been met, the process of structural model evaluation can continue.

3.3.2 Structural Model

The structural model refers to the component of the overall model that focuses on the relationships between latent variables. The structural model, the inner model in PLS-SEM, tests hypotheses about the relationships between constructs or latent variables. The structural model in PLS-SEM consists of the paths or arrows representing the hypothesized relationships between the latent variables. These paths indicate one construct's directional influence or impact on another. The structural model is developed based on theoretical considerations, prior research, and the specific hypotheses being tested. It is an essential part of the PLS-SEM analysis as it allows researchers to examine the relationships between constructs and assess the overall theoretical model, both direct and indirect relationships involving mediating and moderating variables. Mediation occurs when a third variable (the mediator) intervenes in the relationship between an independent variable (exogenous construct) and a dependent variable (endogenous construct). It explains the process through which the independent variable influences the dependent variable. Mediation analysis focuses on understanding the indirect effects of the independent variable on the dependent variable through the mediator. Moderation, on the other hand, involves the influence of a third variable (the moderator) on the relationship between an independent and dependent variable. It examines how the strength or direction of the relationship between the independent and dependent variables varies depending on the different levels of the moderator. Mediating and moderating variables play complementary roles in PLS-SEM structural model evaluation. Mediation explains the process through which relationships occur, while moderation identifies the conditions under which relationships vary. Including mediating and moderating variables in the research model enhances understanding, improves model fit, and contributes to theory development and testing. At this stage, the structural model evaluation includes the evaluation of the model itself and the assessment of the goodness of the model (goodness-of-fit) using several criteria to assess the predictive capabilities of the model and the relationship between latent variables (Hair et al., 2017; Hair et al., 2018; Henseler et al., 2017).

Researchers can carry out the structural model analysis process on SmartPLS if the research model at the measurement evaluation stage has met all the criteria. Next, select the research model and do the "calculate" process by selecting "bootstrapping." Then select "basic settings" with 5000 times subsamples (larger bootstrap subsamples increase the computation time). In "Advanced Settings" for "Confidence Interval Method," select Bias-Corrected and Accelerated (BCa) Bootstrap and then "Start calculation." Bootstrapping results will provide information about final results, histograms, and databases.

1. Structural Model Evaluation

First, researchers must assess collinearity to ensure it does not introduce bias into the regression results. This assessment process resembles the evaluation of formative measurement models, but it involves using the latent variable scores of the exogenous constructs to calculate the VIF values. VIF values exceeding 5 suggest potential collinearity issues among the predictor constructs. Ideally, VIF values should be close to 3 or lower (Hair et al., 2019). In cases where collinearity is problematic, a commonly employed approach is to develop higher-order models that align with established theory (Hair et al., 2017). In "PLS Algorithm," see "Quality Criteria" and select "Collinearity Statistic (VIF)," then select "Inner VIF Value." If the VIF value is green, it indicates that the VIF value is three or lower, indicating no multicollinearity. However, researchers can consider the value of VIF 5 or below according to the recommendations of Hair et al. (2019).

Second, researchers assess direct and indirect influences to answer research hypotheses by evaluating the significance value of relationships between variables from bootstrapping results. See "Path Coefficient" in Final Results to evaluate the direct influence between variables. Researchers will get information related to the value of the original sample (O), Sample Mean (M), Standard Deviation (STDEV), Statistical T (IO / STDEVI), and p-value. If the t-statistical value is more than 1.96 (t-table) and the p-value is smaller than 0.05, it indicates a significant influence between research variables. The effect can be positive or negative, as seen from the value of the path coefficient or O. In addition, researchers need to assess the "Confidence Interval" on the "Path Coefficient" and display information on the lower and upper limit values of the 95% confidence interval.

While on indirect effects involving mediating or moderation variables, select "Specific Indirect Effect" in "Final Result." Researchers will get the same information as the "Path Coefficient" display. The assessment is also no different from the assessment of direct influence, where if the t-statistical value is more than 1.96 (t-table) and the p-value is smaller than 0.05, it proves that there is a significant role of mediating or moderating variables in the influence between exogenous and endogenous variables. 95% confidence interval information for lower and upper bound values needs to be submitted to the research report. This information can be obtained in "Confidence Interval" in "Specific Indirect Effect." The confidence interval value at the 95% confidence interval shows the range of the lowest to highest level of influence of the exogenous variable on the endogenous variable. The analysis also shows the range of influence for mediating and moderation variables.

2. Model Goodness Evaluation

First, evaluate the model's explanatory power by examining the R^2 value of endogenous constructs. The R^2 measures the variance explained by each endogenous construct and measures the model's explanatory power. It is also referred to as in-sample predictive power (Rigdon, 2012), and its values range from 0 to 1, with higher values indicating greater explanatory power. In SmartPLS, the R^2 value can be seen from the "PLS Algorithm" results on "R square" in "Quality Criteria". As a general guideline, R^2 values of 0.75, 0.50, and 0.25 can be considered substantial, moderate, and weak, respectively (Henseler & Sarstedt, 2013). A value of R^2 greater than or equal to 0.90 suggests overfitting (Hair et al., 2019). However, acceptable R^2 values depend on the context, and in some fields, an R^2 value is as low as 0.10 (Raithel et al., 2012).

Second, the evaluation of the effect size of the direct relationship. This evaluation is quantified by the f^2 effect size, indicating the extent to which the exogenous variable can influence the endogenous variable and the robustness of the model in describing that influence. As a general guideline, values higher than 0.02, 0.15, and 0.35 represent small, medium, and large f^2 effect sizes, respectively (Cohen, 1988; Joe F Hair et al., 2019). The effect size value can only be interpreted to understand the effect size of the direct relationship between exogenous and endogenous variables. In SmartPLS, this f^2 effect size information can be seen in the results of the "PLS Algorithm" in "f square" in "Quality Criteria." Effect size involving mediating variables is not in the SmartPLS results, so the evaluation of the mediating effect size uses the upsilon statistical value (v) where v values higher than 0.02, 0.075, and 0.175, respectively, represent low, moderate, and high mediation size effects (Lachowicz et al., 2018). The effect size value of the moderating variable can be seen in the same way as the information on the effect size value of the direct relationship. However, the moderation size effect value refers to values higher than 0.005, 0.01, and 0.025, respectively, representing low, moderate, and high effects (Kenny, 2018).

Third, evaluating the predictive accuracy of the PLS path model is through the computation of the Stone-Geisser's Q² value (Geisser, 1974; Stone, 1974). This metric is derived from the blindfolding procedure, which involves the removal of individual points from the data matrix, substituting the removed points with the mean, and estimating the model parameters (Sarstedt et al., 2014). Consequently, the Q² does not solely measure out-of-sample prediction but integrates aspects of out-of-sample prediction and in-sample explanatory power (Sarstedt et al., 2021). The blindfolding procedure predicts the removed data points for all variables. Minor disparities between the predicted and original values result in a higher Q² value, indicating enhanced predictive accuracy. To get the Q² value on SmarPLS, the researcher performed a "calculate" on "blindfolding" to produce a "Construct Crossvalidated Reducancy" output that showed the value of "Q² (=1-SSE/SSO)". If Q² values exceed zero for a specific endogenous construct, signifying the predictive accuracy of the structural model for that construct. Generally, Q² values higher than 0, 025, 0.15, and 0.35 represent the PLS-path model's small, medium, and large predictive relevance (Hair et al., 2017).

Fourth, the SRMR (Standardized Root Mean Square Residual) approach measures the discrepancy between the observed and the model's implied correlation matrix. A goodness-of-fit (GoF) measure assesses the model's overall fit. The SRMR approach quantifies the average difference between the observed and predicted correlation matrix, standardized by the average residual correlation. The SRMR values range from 0 to 1, with lower values indicating better model fit. A commonly used guideline is that an SRMR value of 0.08 or lower indicates an acceptable model fit (Henseler et al., 2014). Schermelleh-engel and Moosbrugger (2003) stated that the SRMR value should be between 0.08 and 0.10 to obtain an acceptable fit model. However, it is essential to note that the SRMR approach does not apply to PLS-SEM models because the algorithm for obtaining PLS-SEM solutions is not based on minimizing the divergence between observed and estimated covariance matrices, which is the basis of the SRMR approach (Henseler et al., 2017). Therefore, the SRMR approach should be used with caution in PLS-SEM applications. The SRMR value of SmarPLS is seen in the "Estimated Model" column of "Model Fit" in "Quality Criteria." In addition to the SRMR value, researchers can consider the Normed Fit Index (NFI) value to evaluate the model's goodness. The accepted NFI value exceeds 0.95 (Hu & Bentler, 1999). Hair et al. (2017) suggested not using the GoF criterion due to the fact that it does not represent the goodness of the model in PLS-SEM. GoF also cannot be applied to formative measurement models.

Fifth, evaluate the predictive power of the PLS-SEM model through the PLSpredict approach. Its significance lies in its ability to assess the model's out-of-sample prediction performance, which is crucial for understanding how well it can generalize to new data. PLSpredict allows researchers to go beyond determining the model's fit to the observed data and evaluate its ability to make accurate predictions on new, unseen data. To get the PLSpredict value on SmartPLS, researchers conducted a "calculate" research model by selecting "PLS Predict" to produce "MV Prediction Summary" information. At this stage, compare the values of Root Mean Square Error (RMSE) or Mean Absolute Error (MAE) in PLS and RMSE or MAE in LM (linear regression). In comparing the RMSE (or MAE) values with the LM values, the following guidelines apply (Shmueli et al., 2019): If the PLS-SEM analysis, compared to the naïve LM benchmark, yields higher prediction errors in terms of RMSE (or MAE) for all indicators, this indicates that the model lacks predictive power. The model has a low predictive power if most of the dependent construct indicators in the PLS-SEM analysis produce higher prediction errors than the naïve LM benchmark. If the minority (or the same number) of indicators in the PLS-SEM analysis yields greater prediction errors than the naïve LM benchmark, this indicates a medium predictive power. If none of the indicators in the PLS-SEM analysis has higher RMSE (or MAE) values compared to the naïve LM benchmark, the model has high predictive power.

Finally, a robustness check is performed by paying attention to nonlinear effects, endogeneity, and unobserved heterogeneity (Sarstedt et al., 2019). Robustness checks are an essential component of PLS-SEM analysis, as they help ensure the model's results are reliable and consistent. By conducting these checks, researchers can have greater confidence in the validity and generalizability of their findings and can make more informed decisions based on the model's results (Hair et al., 2019). First, unobserved nonlinearity refers to the potential existence of nonlinear relationships between variables not considered in the model. It is important to ensure that the model's assumptions about linear relationships between variables are valid. This process accurately captures the true nature of the relationships between variables and makes reliable predictions based on the model. In SmartPLS, select "Quadratic Effect" and then select the entire relationship line from several exogenous to endogenous variables. Do the same if the research model has multiple endogenous variables. Then select "calculate" and "bootstrapping" so that "Path Coefficient" will appear. In this display, researchers pay attention to the Quadratic Effect (QE) value of each relationship between exogenous variables and endogenous variables. If the P Value indicates red or greater than 0.05 or insignificant, it can be concluded that there is a linear effect between exogenous and endogenous variables. Second, endogeneity occurs when a predictor variable is correlated with the error term in a regression model, leading to biased and inconsistent parameter estimates. Checking for endogeneity is important to ensure that the relationships between variables are accurately captured and that the model's results are not influenced by endogenous factors. To evaluate endogeneity in PLS-SEM using the Gaussian copula analysis approach (Hair et al., 2018). In SmartPLS, select "Gaussian Copula" then select the relationship line between exeogen to endogenous variables. Then select "calculate" and "bootstrapping" so that "Path Coefficient" will appear. Pay attention to the p-value Gaussian Copula (GC) value; if it is red, greater than 0.05, or insignificant, it can be concluded that there is no endogeneity problem. Do it gradually; for example, if there are 2 exogenous variables and 1 endogenous variable, then Gaussian copula analysis is carried out 3 times, namely on the relationship line of exogenous variable 1, the relationship line of exogenous variable 2, and the relationship line of exogenous variables 1 and 2. Third, heterogeneity effects refer to the potential presence of unobserved differences or variations in the relationships between variables across different subgroups or segments of the data. Checking for heterogeneity effects is important to ensure the model's results are robust and generalizable across different population segments. Evaluation of heterogeneity effects on SmartPLS using Finite mixture partial least squares (FIMIX-PLS) approach. Heterogeneity effects testing is better for large samples, considering that this test will divide the sample into several segments. FIMIX-PLS segmentation is a method to uncover unobserved heterogeneity in the inner (structural) model. It captures heterogeneity by estimating the probabilities of segment memberships for each observation and simultaneously estimates the path coefficients for all segments. In SmartPLS, do the calculation by selecting "Finite Mixture (FIMIX) Segmentation," then in "Basic Setting," input the number of segments in "Number of Segments" (determining the number of segments can be done by dividing the number of samples by the minimum number of samples specified) by "Maximum Iterations" 5000 times and "Number of Repetitions" is 10 times. Repeat from the highest segment number to segment number 1. The results of this process will be displayed in "Fit Indices" in "Quality Criteria" by providing information on the values of AIC (Akaike's Information Criterion), AIC3 (Modified AIC with Factor 3), AIC4 (Modified AIC with Factor 4), BIC (Bayesian Information Criteria), CAIC (Consistent AIC), HQ (Hannan Quinn Criterion), MDL5 (Minimum Description Length with Factor 5), LnL (LogLikelihood), EN (Entropy Statistic), NFI (Non-Fuzzy Index) and NEC (Normalized Entropy Criterion). The Fit Indices value information of each segment is collected in 1 table to see how the values of each segment compare. Heterogeneity effects are shown in the AIC3, AIC4, BIC, CAIC, and EN values. Researchers noticed the consistency of AIC3 and CAIC, AIC3 and BIC, IC4 and BIC in 1 segment. In addition, EN must be at least 0.50 or greater. The evaluation is continued from the "Segment Sizes" information in the "Final Results" to obtain consideration of the relative segment sizes of the FIMIX-PLS solution for a certain number of predetermined segments. The value of segment sizes from the analysis of each segment number is collected in 1 table, and then observations are made on segments that have the best possibility to guarantee a valid analysis (Hair et al., 2018; Sarstedt et al., 2019).

4. Conclusion

This study provides practical guidance for researchers conducting multivariate social sciences research in PLS-SEM analysis using SmartPLS. Researchers with limited knowledge of the PLS-SEM method can use SmartPLS to obtain valid analysis results. The findings indicate the importance of researchers reporting relevant reasons for using PLS-SEM. Several of the underlying points that are presented and explained in the research methodology include research objectives that explore theoretical extensions for theory development from a predictive perspective, populations with small samples that tend to be non-normally distributed, a constellation of research variables that shows a complex structural model with reflective and or formative approaches in first order or second order that requires latent variable scores, primary or secondary data sources with the possibility of not having comprehensive evidence based on measurement theory, instruments that were tested for validity and reliability, and research data analysis using SmartPLS with measurement criteria. PLS-SEM analysis evaluates the measurement model (outer model) and structural model (inner model). The criteria for evaluating the reflective measurement model consist of reflective indicator loadings referring to the outer loading value, internal consistency reliability referring to the consistency reliability (CR) value, convergent validity referring to the AVE value, and discriminant validity with the HTMT approach. While evaluating the formative measurement model, which consists of convergent validity with redundancy analysis, the relevance of the indicator weights refers to the outer weight value, and collinearity refers to the VIF value.

The structural model evaluation consists of evaluating collinearity referring to the VIF value, significant research models referring to the p-value, effect size f square for direct effects and upsilon statistical value for the effect size of indirect effects involving mediating variables, R square value, Q square through blindfolding procedures, SRMR value, PLSpredict, and robustness check by paying attention to the nonlinear impacts, endogeneity, and unobserved heterogeneity. Although this research contributes significantly to understanding PLS-SEM analysis, it also has limitations. The study only analyzes the application of SmartPLS software to obtain output results according to the needs of PLS-SEM analysis. Further studies using other software must be done to compare comprehensively. In addition, case examples can be added to make the analysis more straightforward to understand.

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