

Steps in Research Process (Partial Least Square of Structural Equation Modeling (PLS-SEM))

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Abstract

Data Analysis is the process of methodically applying statistical and logical methods to describe and explain, condense, recap, and evaluate data. Data analysis refers to the process of developing answers to research questions through the examination and clarification of data. The very basic steps in the analysis process are to recognize problems, determine the availability of appropriate data, decide on which methods are suitable for answering the research questions, apply the methods and estimate, summarize and discuss the results. The design and analytical path of any research program should have a specific methodological direction based on its research objective and framework. This study is a review, analysing data from studies that utilize a quantitative method, follow a survey method design and apply Partial Least Square of Structural Equation Modeling (PLS-SEM). The quantitative approach is also known as a traditional, positivism, experimental or empiricist research approach. This study aims to review all the steps that need to be carried out before applying SEM using SPSS and after this, all the steps of SEM need to be reported.

Keywords: Data Analysis, Methodology, Quantitative, Partial Least Square of Structural Equation Modeling (PLS-SEM), SPSS

Introduction

The quantitative methodology can measure specific characteristics by the use of structured data collection method from a large number of sample representatives, therefore, the results can be proposed to the whole population easily and precisely (Creswell, 2014). For the means of collecting primary data and based on the deductive approach of this study and a need for a large number of participants, the quantitative method for data collection was chosen. According to Creswell (2014), the deductive approach is normally used in the quantitative research method because hypothesised relationships should be clear; in search for observable and quantifying outcomes. In fact, the quantitative research approach scientifically provide an actual answer to the research question which was defined in an objective way and measured through statistical tools and techniques (Johnson, 2001).

It is very common in organisational psychology to use questionnaires for collecting data, and the main reason is that it is easier to perform (Sekaran, 2006). This method is also appropriate for the present study since it enables the collection of data from a large sample size which helps the researcher in testing research suggested hypotheses and the generalisation of the results. One of the main advantages of the use of questionnaires is that it facilitates the collection of a large number of data in a relatively short time. The questionnaire is one of the main instrument for gathering statistical information based on attributes, attitudes or actions of a population. According to Sekaran (2006), a questionnaire helps the researcher to measure individual and organisational attitudes, opinions and practices; it also enables the researcher to identify and describe the validity in various phenomena. Furthermore, researchers can use questionnaires for descriptive and explanatory studies and explain the relationships between variables; particularly in cause and effect relationships.

Pretesting the Questionnaire

The very first step before analysing data is to convert raw data into a format suitable for decision-making and conclusions. It is required for data to be edited, coded, cleaned, screened and then for further analysis and interpretations, entered into mathematical computer software programs. In fact, the process of preparation of raw data is conducted as the main process for analysis. The proposition of raw data starts with preliminary questionnaire screening. In the following steps, data editing and data coding were performed. The process of data coding was to recognise and categorise each response with numerical scores and signs (Bajpai, 2011). Moreover, for further analyses and interpretations, the data were entered into a mathematical computer software program and data analysis strategy was initiated. Eventually, the process of data analysis aided the researcher in familiarising with detailing the datasets and the relationships among constructs (latent variables) under investigation and examination of data (Hair, Black, Babin, Anderson, & Tatham, 2006).

In fact, in the scientific research of the social sciences, the accuracy of the measurement model and the theoretical constructs of the model should be viewed in terms of reliability and validity (Churchill, 1979; Kumar, 2010). As indicated by Churchill (1979), despite the importance of the instrument reliability, it does not necessarily guarantee the validity of the instrument. However, a valid instrument means that the instrument is reliable. Validity is the degree in which an instrument can measure what it was designed and aimed to measure. Reliability refers to the compatibility and stability of a measurement while validity is concerned with the extent of reflection which may be observed from social phenomena (Kumar, 2010; Wahyuni, 2012). The consistency of the measurement will facilitate the repeatability of the study.

Content Validity and Unidimensionality

Validity is a necessity for both qualitative and quantitative researches. According to Cohen, Manion, and Morrison (2007), the validity of the data and measurement in quantitative research methods may be improved through careful sampling, suitable and appropriate instrumentation and statistical attitudes of the data. Brown (1996) mentioned that validity is traditionally subdivided into three categories: content, construct validity (which include convergent and discriminant validity) and criterion-related. Content validity refers to the degree in which a questionnaire's content covers the extent and depth of the topics it was intended to cover. Failure to establish content validity will invalidate the instrument results because it shows that the instrument does not reflect the full domain of the construct. In the SEM approach, unidimensionality can be achieved in a condition where the factor loading of the measuring items for the respective latent construct is acceptable. In fact, factor loading which is too low should be removed for the model to be unidimensional. Often for most of the studies the researcher needs to determine the content validity through: 1) conducting a comprehensive and systematic database in literature review; 2) reviewing of items with experts (pre-test); 3) conducting a pilot test; and 4) purifying the items using coefficient alphas and factor analysis (Churchill & Iacobucci, 1999; Wahyuni, 2012). Upon achieving the content validity, the reliability of the measurement has to be identified.

Construct Validity

Construct validity, together with convergent validity and discriminant validity, assess the degree to which a measurement is represented and logically concerned. Construct validity refers to the degree in which a test measures an intended hypothetical construct (Kumar, 2005). For establishing the construct validity, the researcher must ensure that the construction of a particular subject agrees with other constructions of the same fundamental subject or issue. Evidence of construct validity includes the theoretical and empirical support for the explanation and understanding of the construct. This series of evidence includes the statistical analysis of the internal construction of the test (such as relationships between responses to different questions) and relationships between the test and measures of other constructs. This can be obtained through correlations with other measures and methods of the issue or by rooting the structure of the research in a large exploration of literatures which points out the connection and meaning of a particular construct (such as a theory of what that construct is) and its component elements (Cohen et al., 2007; Kumar, 2010).

Convergent and discriminant techniques are two types of construct validity in the SEM method (Thyer, 2010). Convergent validity can be defined when indicators or items of a specific construct converge or share a high proportion of variance (Hair, Black, Anderson, & Tatham, 2009). A convergent validity problem means that the variables do not correlate well with each other within their parent factor: i.e., the latent factor is not well explained by its observed variables.

Convergent method means that a different technique for investigating the same construct should provide a relatively high inter-correlation, where discriminant techniques propose that using similar techniques for investigating different constructs should give relatively low inter-correlations. Such discriminant validity may also be provided by factor analysis, which collects similar issues together and separates them from others (Cohen et al., 2007). As indicated in previous studies, when all questions used in the study are taken from validated, previously established and well-accepted instruments, the validation procedures, such as construct validity and criterion-related validity, are not required (Ong, 2012; Venkatesh, Morris, Davis, & Davis, 2003).

Goodness of Data

Data Screening and Preparing

The very first step after collecting data was to purify the data so that they provide meaningful and reliable results when analysed (Fidell & Tabachnick, 2012; Hair et al., 2009). In fact, the raw data were subjected to editing in order to discover any errors and omissions, and to correct them if possible. As indicated, the process of editing raw data checks and adjusts data for omissions, reliability and consistency before coding and later transferring to data storage and analysis procedures (Hair, Hult, Ringle, & Sarstedt, 2014; Sekaran, 2003; Ticehurst & Veal, 2005). After receiving, the completeness of the survey questionnaires and eligibility of respondents were checked by the researcher. Then, the process of data coding identified and categorised each response with numerical scores and symbols (Cooper & Schindler, 2006; Ticehurst & Veal, 2005; Zikmund, Babin, Carr, & Griffin, 2012). Subsequently, the process of cleaning and screening data needs to be coded, consistent and checked for missing values (Fidell & Tabachnick, 2012; Hair et al., 2009; Manning & Munro, 2007). In the final step, to obtain descriptive and inferential statistical analyses, to summarise data and information, to examine the research questions and to hypothesise the measured model, the data needs to be entered into computer statistical software programs (i.e., SPSS 20.0 and Smart-PLS 3) (Manning & Munro, 2007; Tabachnick & Fidell, 2001).

Method to Handel Missing Values

The data analysis was proceeded with the examination of data entry and handling of missing data and values. This was significantly related to achieve some critical perceptions about the data characteristics and analysis (Hair et al., 2014). In fact, in the processes of data cleaning, screening data must be coded, consistent and checked for missing values and responses in the returned survey questionnaires. These processes improved the validity and accuracy of data analysis and ensured that assumptions for data analysis methods were not (Hair et al., 2006; Tabachnick & Fidell, 2001). Missing data and value is one of the most pervasive issues in data analysis. As indicated by Hair et al. (2014), missing data and values occur when a respondent either intentionally or unintentionally fails to answer one or more question(s). However, once the amount of missing data on a questionnaire goes beyond 15%, the observation needs to be omitted from the data file (Hair et al., 2014) before starting the analysis. This process must be done manually.

In terms of handling missing values, SPSS software has the option with different ways such as mean, median, linear trend and linear interpolation. However, Expectation-Maximization Algorithm is the second best way to replace values in SPSS, especially when there are few numbers of missing points in the data set (Little & Rubin, 2002). Therefore, Expectation-Maximization Algorithm was used in this study for handling the missing values. Before entering new data points in missing cases, it is required to test an important Little's Missing Completely at Random (MCAR) Test to demonstrate whether data were missing completely randomly or non-randomly at first, before replacing missing values. Little's Missing Completely at Random (MCAR) Test is a statistical test which was provided by Little and Rubin (2002). In fact, MCAR test is a Chi-Square test which stands for 'missing completely at random' and it is a test that researchers need to perform before doing anything with the missing values and data. A significant value indicates that the data are not missing completely at random (Little & Rubin, 2002). The result of the Chi-Square showed that the significant value was greater than .05; a value lower than .05 indicates that data are not completely missing at random. The next step after this was to use a suitable technique to replace the missing data.

Upon completion of data entry and recoding processes, calculation of reliability and validity of all measures were undertaken through purification. According to Sekaran (2003), it is important to assess the "goodness" of the measures developed in some way. In fact, the researcher should be assured that the instrument used in the study precisely measures the study variables. The technical value of any study can be determined by measuring the quality of the validity and reliability of the used instrument.

Data Normality Test

Following the replacement of missing data, the scale data was evaluated to determine the normality of distribution. Because of the assumption that factor analysis and structural equation modelling both need variables to be normally distributed, it was required to check the distribution of variables to be used in the analysis. The normality of data could be tested by estimating the value of skewness and kurtosis for the distribution of scores of latent variables. To check whether the skewness and kurtosis values were significantly deviated from normal distribution, each skewness and kurtosis values were divided by their own standard error (Manning & Munro, 2007; Tabachnick & Fidell, 2001).

PLS technique does not consider normality; and thus, to obtain standard errors for testing research hypotheses, it uses bootstrapping. Instead, it supposes that the distribution of the sample is a rational and sensible representation of the considered distribution of population (Hair *et al.*, 2011). Even if scores transformation improved normality by itself, it may not be helpful or beneficial for improving and refining the model as a whole (Gao, Mokhtarian, & Johnston, 2008). So, the original untransformed and unchanged scores of latent variables were used in the subsequent Partial Least Squares (PLS) procedure analysis in this study. The Kolmogorov-Smirnov test and Shapiro-Wilks test were used to test normality distribution by comparing the research data to a normality distribution with the similar standard deviation and mean as in the research sample (Mooi & Sarstedt, 2011).

After the replacement of missing data, the scales data were measured to determine normality of distribution. For large sample size, the statistical methods that measure normality often start with assesses of skewness and kurtosis. In fact, to realise whether normality exists, the researcher needs to examine the distribution of skewness and kurtosis for each observed variable (Weston & Gore, 2006). Therefore, these tests were adapted to test the normality distribution of data in this study. Skewness and kurtosis are statistical approaches for measuring the symmetry (skewness) and peakedness (kurtosis) of a distribution (Fidell & Tabachnick, 2012; Meyers, Gamst, & Guarino, 2012). Normality distribution of data is balanced and organised, which has a skewness of zero. A distribution with positive skewness represents a few cases with large values that lengthen on the right side; and negative skewness represents a few cases with small values that lengthen on the left side of the distribution (Fidell & Tabachnick, 2012; Meyers *et al.*, 2012). Kurtosis is a degree of the general peakedness of a distribution. Positive kurtosis, also known as leptokurtosis, suggests an extreme peak in the centre of the distribution (too peaked); negative kurtosis, which is also known as platykurtosis, indicates an enormously flat distribution (too flat) (Fidell & Tabachnick, 2012; Meyers *et al.*, 2012). The skewness and kurtosis were computed by SPSS 21.0. This produced a z-score (i.e., standardised score) which is based on the number of standard deviation of above or below the mean if it exceeded an absolute value that is changed in varied samples.

Test of Non-Response Bias

Non-response bias is one of the challenges in generalising results of the study, which is conducted on the usable response after gathering data. In statistical surveys, non-response bias occurs when the answers of respondents to a survey are different from the potential answers of those who did not answer in terms of demographic or attitudinal variables (Sax, Gilmartin, & Bryant, 2003). Non-response bias could be categorised as unusable answers which occur when respondents refuse to participate or simply discontinue answering questions, or they may refuse to answer particular questions but continue with others. Moreover, a high rate of non-response could increase the possibility of statistical biases, and any level of non-response may cause the non-response bias in the evaluations of the survey questionnaires (Baruch & Holtom, 2008).

According to Weiss and Heide (1993) in their organisational study, the first 75% of companies returning the survey questionnaires are considered as early-responders, while the last 25% of companies would be defined as late-responders and representatives of companies that did not answer the survey questionnaires. Using an independent samples *t*-test ($t < 0.05$), early and late respondents to the survey questionnaires were compared on a number of key characteristics. The Levene's test for homogeneity of variances was also not significant with (sig. or $p > 0.05$) and the *t*-value was statistically not significant with $t < 0.05$.

Outlier Identifications

Outliers are different observations from the main data falling outside the control line. In fact, statistical inferential tests could be very sensitive to outliers, usually because the estimations rely on squared deviations from the mean. One or two values that are far from the mean can alter the results considerably.

In some cases, the study results can significantly change when one or two values are far from the mean (Tabachnick & Fidell, 2001). Outliers can be either univariate with the maximum or highest score pattern on a single latent variable, and/or multivariate with an uncommon score through a range of various latent variables (Ben-Gal, 2005; Hair et al., 2006; Petrie & Sabin, 2013). There are two reasons behind the existence of univariate and/or multivariate outliers: 1) an unusual pattern of cases compared to the rest of the cases and/or 2) an unusual scores combination on two or more latent variables (Tabachnick & Fidell, 2001).

Handling outliers is an important issue in examining data because it might have important and negative effects on the result of data analysis (Hair et al., 2009). An outlier refers to an examination that is statistically far in comparison to the rest of the research data set (Parke, 2013). As suggested by Hair et al. (2009), based on their source of uniqueness, outliers are classified in four types. The first model of outliers resulted from a data entry error or mistakes in coding. This type of outlier needs to be eliminated or recoded as missing values. The second type of outliers was derived from an extraordinary event that arises from the uniqueness of observation. The other types result from extraordinary observation that are not explained by the researcher; thus, they could depend on the researcher's decision and judgment. The last and fourth type of outliers is derived from ordinary values, which differ within the normal scope or filed values on all variables. They are not extremely high or low values on the variable but their combination of values are unique across variables. This type of outlier should not be eliminated from the analysis until they show that they are not delegated from the population, or seriously deviate from the normal (Hair et al., 2009).

Hence, the first step in facing the outliers was to identify them. To identify outliers in a large sample size of 80 and above, a standardised score value of ± 3 was suggested to be used (Hair et al., 2009). Based on this standard, to identify outliers in this study, the data were examined for all variables through SPSS 21.0. Data were recognised by adopting the standard score, which have a mean of 0 and a standard deviation of 1. However, if the outliers within the data appeared to be in type four (as mentioned by Hair *et al.*, 2009) and there was no error from the data entry or miscoding in the data, the researcher can keep all of them.

Using Structural Equation Modelling (SEM)

The SEM method is one of the most important components of applied multivariate statistical analyses. This technique has been employed by many researchers in different fields such as biologists, economists, educationalists, marketing, medical and a variety of other social and behavioural scientists (Anderson & Gerbing, 1988). In fact, SEM can be seen as a statistical procedure that takes a confirmatory method (i.e., hypothesis-testing) to the analysis of a structural theory on a given phenomenon (Byrne, 2013a). Usually, SEM can be seen as a theory that reveals "causal" techniques that present observations on multiple variables (Gefen, Straub, & Boudreau, 2000; Hair, Ringle, & Sarstedt, 2011). This technique represents two essential concepts: a) that a group of structural (i.e., regression) equations, by considering the measurement error, provide the studied causal processes, and b) that these structural relations can be modelled visually to simplify and facilitate a clearer conceptualisation of the theory and studied hypotheses (Roldán & Sánchez-Franco, 2012; Wong, 2013).

One essential factor for both the researcher and reader is the description of the analysed data. Moreover, in both quantitative and qualitative approaches, the reduction of a large amount of data to a comprehensible summary is a significant function (Black, 1999). Descriptive statistics are used to provide quantitative descriptions in a manageable structure and reduce many numeric data into a simple summary. Descriptive statistics deals with the presentation of numerical data, in form of tables or graphs, and with the methodology of analysing the data. They allow researchers to summarise and describe the collected numeric data in a way in which readers can easily understand the results (Black, 1999; Fraenkel, Wallen, & Hyun, 2011).

SEM is a considerably complex statistical method for assessing relations between constructs, including latent and observed variables. Latent variables refer to the conceptual terms that are employed to show the theoretical concepts. These variables in the model are graphically symbolised by a circle. Observed variables refer to items, measures and indicators of variables that are measured directly and graphically represented by a square in the model (Andreev, Heart, Maoz, & Pliskin, 2009; Fornell & Larcker, 1981). Latent variables can be exogenous (independent variables), or endogenous (dependent variables). In fact, a latent variable is defined as a hypothetical construct or an unobservable variable, which is a theoretical concept that is not directly measurable, however, is a useful concept. A latent variable can only be derived and concluded from multiple measured variables, which are also known as manifest variables, indicators, items or observed measures (Fornell & Larcker, 1981).

The literature review on SEM distinguishes between two different operationalisation of the relationships between constructs/latent variables and their observed indicators: 1) the reflective indicators/main factor, and 2) the formative indicators/composite index measurement models of the latent variable (Coltman, Devinney, Midgley, & Venaik, 2008; Diamantopoulos & Siguaw, 2006; Hair et al., 2014).

Reporting the Result of Structural Equation Model

The estimation of a model delivers empirical measures of: 1) the relationships between the indicators and the constructs (measurement models or outer model) and 2) the relationships between the constructs (structural model or inner model) (Byrne, 2013b; Hair et al., 2014). The empirical measures allow the researcher to compare the theoretically established measurement and structural models with reality, as represented by the sample data. In other words, the empirical measures enable the researcher to determine how well the theory fits the data. Therefore, using PLS-SEM enabled the researcher to measure the model's predictive potential and competences to judge the quality of the model (Hair et al., 2014). In general, Structural Equation Model (SEM) is composed of two sub-models, the measurement model and the structural model (Hair et al., 2014; Jung, 2007). The measurement model identified the nature of the relationship between the manifest indicators and latent variables. The structural model identified the causal relationships among the latent variables. It also specified whether particular latent variables directly or indirectly affect certain other latent variables in the model (Byrne, 2013b; Jung, 2007; Weston & Gore, 2006).

Table1. Systematic evaluation of PLS-SEM results

Systematic Evaluation of PLS-SEM Results	
Step 1: Evaluation of the Measurement Model	
Stapes 1a: Reflective Measurement Model	Stapes 1b: Formative Measurement Model
Internal Consistency	Collinearity among Indicators
Construct Validity	Significance and Relevance of Outer weights
Discriminant Validity	
Step 2: Evaluation of Structural Model	
Collinearity Assessment	
Structural Model Path Coefficients and Hypothesis Testing	
Coefficient of Determination (R ² Value)	
Effect size F ₂	
Predictive Relevance Q ₂	

Reflective versus Formative Indicators

SEM includes two parts: a “Measurement Model” where one tests the relationship of an unobserved variable (a latent variable or a construct) with a set of observed variables (indicators or measured variables); and a “Structural Model” or a “Path Model”, where causal relationships among latent variables and/or measured variables are tested (Hair et al., 2014; Roy, Tarafdar, Ragu-Nathan, & Marsillac, 2012). A “Measurement Model” can be either “Reflective Measurement Model” (arrows point from the LV to the measured indicators) or a “Formative Measurement Model” (arrows point from the measured indicators to the LV) (Bollen & Lennox, 1991; Hair et al., 2014). Wrongly modelling a reflective model as formative, and vice versa, is known as “model misspecification”. Reflective models have their foundation in the classical test theory (Bollen & Lennox, 1991). Formative or causal index results expect the opposite direction of causality from the indicator to the construct (the indicators cause the latent variable); such that the content of the indicators define the meaning of the latent variable. While the reflective view dominates the psychological and management sciences, the formative view is common in economics and sociology (Coltman et al., 2008). The choice of a formative versus a reflective specification thus depends on the casual priority between the indicators and the latent variable (Bollen & Lennox, 1991).

There are two statistical methodologies to assess SEM with constructs including formative measurement models: covariance-based (CB-SEM) and partial least squares path modelling (PLS-PM) or variance-based SEM (Ringle, Götz, Wetzels, & Wilson, 2009).

Variance-Based SEM: Partial Least Squares

There are some differences between SEM and the first-generation regression tools which include: 1) relationships among multiple predictor and criteria variables, 2) unobservable latent variables, 3) errors in observed or latent variables, and 4) statistically, a priori testing of theoretically substantiated assumptions against empirical data (i.e., confirmatory analysis) (Chin, 1998a). The covariance-based SEM (CB-SEM) technique, traditionally known as the best SEM method, is popular among many research fields which is applicable by a wide range of software programs such as LISREL, AMOS and CALIS. The purpose of CB-SEM is to calculate model parameters that will minimise the difference between the measured and observed covariance matrices, yielding goodness-of-fit indices as a result of the significance of these differences (Andreev et al., 2009; Chin, 1998b). CB-SEM attempts to calculate model parameters that will minimise the difference between the calculated and observed covariance matrices, yielding goodness-of-fit indices because of the magnitude of these differences (Andreev et al., 2009).

The component-based SEM technique, also referred to as the Partial Least Squares (PLS) method, is a distribution-free method that might be presented as a two-step technique (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005). The first step refers to path measures of the measurement (outer) model used to calculate IV (independent variable) scores. The second one refers to path measures of structural (inner) model, where Ordinary Least Squares (OLS) regressions are performed on the LV (latent variable) scores for measuring the structural equations. The PLS approach was used to maximise the variance of all dependent variables instead of using the model to explain the covariance of all the indicators (Henseler, Ringle, & Sinkovics, 2009). When using SEM, a researcher has the choice of applying CB-SEM or PLS-Path Modelling (PLS-PM) (Chin, 1998b; Ringle, Sarstedt, & Straub, 2012).

Therefore, PLS is mainly considered for prediction purposes, while CB-SEM is focused on parameter assessment. As a result, PLS and CB-SEM techniques differ in terms of objectives, assumptions, parameter measures, latent-variable scores, implications, knowledge of the relationship between a latent variable and its measures, model complexity and sample size (Andreev et al., 2009). Thus, parameter evaluations are created based on the ability to minimise the remaining variances of the dependent/endogenous (latent and observed) variables (Chin, 2010; Henseler et al., 2009). Similar to other available software programs, PLS-SEM software also has some disadvantages and advantages. In terms of disadvantages, lack of widespread accessibility is noticeable because the expansion of the PLS software is limited in comparison to the CB-SEM software (Andreev et al., 2009).

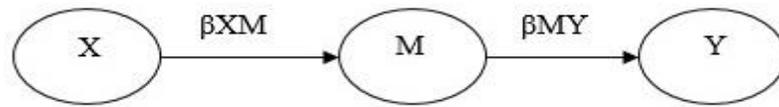
In terms of advantages, compared to CB-SEM, PLS exerts minimal demands on the measurement scale; the required sample size for PLS-SEM analyses is smaller than for CB-SEM (Henseler et al., 2009). PLS-PM can handle a large number of latent variables, it uses simpler algorithms since the PLS structure is obvious; therefore, estimations of latent variables are more practical. PLS also tolerates the creation of a complex conceptual framework from the multi-block analysis, and it facilitates the work of assessing all the formative latent variables (Hair et al., 2014; Ringle et al., 2012). Moreover, in addition to these advantages, the most noticeably cited reasons for using PLS refer to small sample sizes, non-normal data and the use of formatively measured latent variables (Henseler et al., 2009). PLS-SEM can use either a jack-knife or a bootstrap procedure to produce *t*-values and *P*-values for the indicator's loadings (Kock, 2012).

Mediation Relationship

Mediating analysis includes establishing the theoretical indirect relationship between variables. A mediator variable is the variable that causes mediation in the dependent and independent variables. The relationship between the dependent (Y) and independent variable (X) is explained by the mediator variable (Me) (Hair et al., 2011). In fact, the purpose of the mediating analysis was to create a theoretical indirect relationship between the paths and the constructs (Little, Card, Bovaird, Preacher, & Crandall, 2012; Rucker, Preacher, Tormala, & Petty, 2011). More specifically, mediating analysis determines the degree to which indirect effects (through the mediating variables) modify the assumed (hypothesised) direct paths, or relationships. This is done by determining the degree to which indirect effects through the mediating variables modify the direct paths that were hypothesised (Hair et al., 2014).

According to Hair et al. (2014), the focus on mediation are on a theoretically established direct path relationship (between X and Y), as well as, on an additional theoretically relevant component mediator (M) which indirectly provides information on the direct effect via its indirect effect (i.e., $X \rightarrow M$ and $M \rightarrow Y$). Thus, the indirect relationship via the mediator affects the direct relationship from X to Y in the mediator model. This means that variable X is related to variable M and variable M is related to variable Y, then the indirect effects of variable X acting through variable M on variable Y can be suggested (Little et al., 2012) (Figure 1).

Figure 1. The mediating relationship



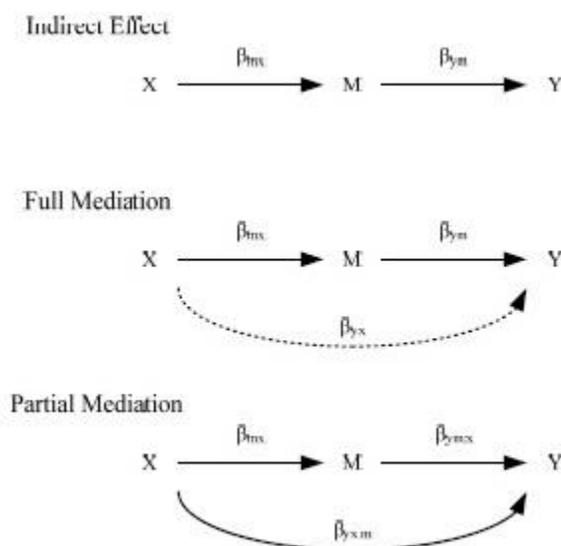
As indicated by Baron and Kenny (1986), in order to express that mediation is occurring, three essential (but not adequate) conditions must be met.

1. Independent variable (X) is significantly linked to mediator (M).
2. Mediator variable (M) is significantly linked to dependent variable (Y).
3. The relationship of X to Y reduces when M is in the model.

In fact, the third condition assumes that the direct relationship between predictor and outcome variables are significant before adding the mediator variable. As indicated by Hair et al. (2014), to estimate the mediation among independent and dependent variables, the first criteria is the direct effect (i.e., distraction and creative outcome path) and should be significant if the mediator is not involved in the model, which is not a necessary condition as suggested by Zhao, Lynch, and Chen (2010). As stated by Hayes (2009), the third condition may not hold all the time, even though the mediation effect still exists. For instance, $X \rightarrow M$ and $M \rightarrow Y$ relationships are both significant, but the direct relationship between predictor and outcome variables ($X \rightarrow Y$) is insignificant because the two path coefficients are in opposite signs and cancel each other out (Hayes, 2009; MacKinnon, Fairchild, & Fritz., 2007).

Therefore, Mathieu and Taylor (2006) introduced three alternative intervening models based on different interactions between predictor, mediator and outcome variables. As shown in Figure 2, the indirect effects model refers to the conditions where only the combined effect ($\beta_{XM} * \beta_{MY}$) is a significant observed relationship which proposes the absence of the total $X \rightarrow Y$ relationship (β_{XY}). Like the indirect effects model, the full mediation model includes significant $X \rightarrow M$ and $M \rightarrow Y$ paths. However, the dashed line from $X \rightarrow Y$ shows a significant total relationship that turns out to be insignificant after adding $M \rightarrow Y$. In other words, in full mediation statement, $\beta_{XY} * M$ needs to be insignificant. Unlike full mediation, a partial mediation indicates that $X \rightarrow M$ path, as well as both $X \rightarrow Y$ ($\beta_{XY} * M$) and $X \rightarrow Y$ ($\beta_{XY} * M$), are significant at the same time.

Figure 2. Alternative intervening models (Mathieu and Taylor, 2006)



Since a mediated casual model includes the hypothesis that predictor variable (X) causes or affect mediator (M) and the hypothesis that variable mediator (M) causes or affect outcome variables (Y), it does not make sense to consider mediator analysis in a condition where one or both of these hypotheses would be nonsense (Little et al., 2012).

This condition was met for all three mediation relationships. In order to assess the mediating hypotheses, bootstrapping techniques (with 5000 resamples) and PLS algorithm were used on the full model to obtain path coefficient and their significant level. The bootstrapping was performed to apply for evaluating the statistical significance of the mediating role (Wong, 2013). As suggested by Hair et al. (2014), the path coefficient for indirect effects or mediators was estimated by the following formula:

$$\text{Path coefficient for indirect effects } (\beta) = \beta_{XM} * \beta_{MY}$$

Moreover, when there are two mediator variables (ME1 and ME2) and they both share the same IV and DV (known as parallel mediation), the following formula will use to calculate the t-value for each relationship.

$$t = \frac{\beta_{XM} * \beta_{MY}}{\text{STDEV}(\beta_{XM} * \beta_{MY})}$$

Moreover, as indicated by Hair et al. (2014) for a two-tailed test, the critical t-value for significant levels of 1% were 2.57 ($\alpha = 0.01$) and 1.65 for significant levels of 10% ($\alpha = 0.10$). As mentioned by Hair et al. (2014), in exploratory researches, a significance level of 10 percent is frequently considered.

For measuring the mediating effect size, this study used the variance that accounted for (VAF) value (VAF = indirect effect/total effect and total effect = indirect effect + β_{XY}) (Hair et al., 2014). As suggested by Hair et al. (2014), a VAF that is above 80% is considered as full mediation, a VAF between 20% and 80% is considered as partial mediation and a VAF below 20% is considered as no mediation.

Global Goodness of Fit (GoF) of the Model

The Goodness-of-Fit (GoF) was used to assess the overall model fit. To measure Goodness-of-Fit, the PLS-SEM has only one method that was defined to be the global fit measure, presented by Tenenhaus et al. (2005). The Goodness-of-Fit was defined as the square root of average R^2 for the endogenous latent variables (reflective) multiplied by the average cross-validated communalities, or the average variances extracted (AVE) values (Tenenhaus et al., 2005).

$$\text{GoF} = \text{square root of: (average AVE) x (average R-squared)}$$

$$\text{GoF} = \sqrt{R^2 * \text{Average Commuality (AVE)}}$$

The GoF values must be at least above 0.1, and depending on the size, values are separated into three categories of large (0.36), medium (0.25) and small (0.10) (Wetzels, Odekerken-Schröder, & Van Oppen, 2009). It was determined that the overall endogenous variable's R^2 average was 0.257, the average variances extracted were 0.614 and the square root of these two multiplied values was 0.397; thus, the model's overall Goodness-of-Fit was shown to exceed the cut-off value of 0.36 for a good model fit. Therefore, according to Wetzels et al. (2009) criteria, the outcome (0.397) illustrated that the model's Goodness-of-Fit measure was large and adequate for global PLS model validity.

Final Thoughts

This paper has reviewed all the steps that need to be carried out before applying SEM-PLS to data analysis. Although there is a vast and valuable body of research on methodology, there is often a need to see all of these steps at the same time. Indeed, this paper was designed to serve as a tool to help researchers to design and conduct excellent research. Therefore after applying all of these steps to the data, the researcher can discuss and report the finding of the study.

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