Quantitative Data Analysis: Choosing Between SPSS, PLS and AMOS in Social Science Research

Mohd Hanafi Azman Ong*
[1]Faculty of Computer and Mathematical Sciences
Universiti Teknologi MARA,
Johor Branch Campus Segamat, MALAYSIA
Email: napieong@uitm.edu.my

Fadilah Puteh
[2]Faculty of Administrative Science and Policy Studies
Universiti Teknologi MARA,
Shah Alam Selangor, MALAYSIA
Email: fadilahputeh@salam.uitm.edu.my

***Corresponding Author**

ABSTRACT
Social science discipline is complex, diverse and pluralistic in nature. There are two widely used research methodologies in conducting social science research namely, qualitative and quantitative research. As both methodologies provide different guidelines for research works, having a clear understanding of the appropriate methodology to be used is essential for researchers. This article discusses the methodological aspects pertaining to quantitative research in social science discipline. Several techniques of quantitative data analysis and software available in social science research are also examined. As quantitative methodology employs numerical data to quantify the social phenomenon, choosing the right techniques enable social scientists to analyse the findings of the study accurately. Quantitative data analysis in social science discipline offers another method of studying the environment around us. It enables the social scientists to measure, analyse and understand the social reality. The main idea of this paper is to offer new and handy information about quantitative data analysis in social science research.

Keywords: SPSS, PLS, AMOS, Social Science, Quantitative Data Analysis.

1.0 INTRODUCTION

Social science as a discipline comprises a number of sub-disciplines ranging from business and management, humanities, arts, political science and education. Just as the science discipline relies on experimental and scientific measurements, the social sciences discipline also employs scientific measurement for more accurate and reliable data analysis. The scientific or quantitative measurements in social science discipline are widely used apart from the qualitative measurement tools to generalize samples of study to a larger population.

Despite the popularity of scientific measures in data analysis, social scientists face dilemmas in selecting the right and appropriate tools to be used. This is because the accuracy of data analysis could be reduced hence, affecting the total outcome of the research. With that in mind, the objective of this paper is twofold, namely to discuss the common statistical analysis and software used in social sciences studies and to suggest the right statistical analysis to be employed.

2.0 TYPES OF STATISTICAL ANALYSIS

Basically, in statistical discipline, two common theories are usually used namely, the comparison statistical analysis theory and correlation statistical analysis theory (Casella and Berger, 2002; Tabachnick and Fidell, 2007). Both statistical theories share some common characteristics of classifications test, which are the parametric and non-parametric techniques (Field, 2009; Pallant, 2015) that rely on general assumptions of the respective statistical tests. In using the comparison and correlational statistical analysis theories, the researchers are familiar with the terms univariate, bivariate and multivariate statistical tests which are based on specific assumptions for conducting these tests (Pallant, 2015).

Univariate analysis refers to analysing one variable at a time (Pallant, 2015). An analysis that involves only one variable (i.e. comparison analysis of one variable against a number of different groups) is known as a univariate statistical analysis. As for bivariate analysis, this relates to analysing two variables at a time (Pallant, 2015; Field, 2009). However, this analysis only exists in the context of relationship analysis, such as correlation analysis. Regarding multivariate analysis, this involves analysing more than one variable at a time (Johnson and Wichern, 2007; Tabachnick and Fidell, 2007; Hair et al., 2010). It could be either causal and effect analysis (i.e. regression analysis) or comparison analysis (i.e. MANOVA).

2.1 Univariate and Multivariate Statistical Comparison Analysis

In statistical comparison analysis, the common method adopted by the researcher to examine the significant differences between two interested groups towards one targeted variable is the independent t-tests (Field, 2009; Pallant, 2015; Bluman, 2012; Kim, 2015). Meanwhile, the one-way ANOVA statistical tool is also a popular statistical method used to measure the significant differences among more than two comparison groups towards one targeted variable (Field, 2009; Pallant, 2015; Bluman, 2012; Kim, 2015). Both tests require that the distribution of the targeted variable must be approximately normally distributed (Field, 2009; Sheridan et al., 2010; Pallant, 2015) and the measurement of the targeted variable to be at least at interval measurement (Field, 2009; Pallant, 2015).Hence, both tests could be classified as parametric statistical methods.

The non-parametric comparison analysis is usually undertaken when the variables do not meet the assumption of normality and the nature of the targeted measurement variable is nominal or ordinal measurements (Wayne, 1990; Field, 2009; Pallant, 2015; Nahm, 2015). If the assumptions of the independent t-tests were not met, the Mann-Whitney comparison analysis is an alternative method for comparing differences between two interested groups towards one targeted variable (Wayne, 1990; Field, 2009; Pallant, 2015). Further, the Kruskall-Wallis comparison analysis test could also be used when the assumption of one-way ANOVA cannot be met (Field, 2009). However, since the one-way ANOVA statistical test is robust towards the assumption of normality distribution, the Kruskall-Wallis statistical test is only conducted when the measurement of the targeted variables is at ordinal level (Wayne, 1990).

In regard to the multivariate statistical comparison analysis, careful planning of research designs is required if researchers intend to use this type of analysis. The reason being the non-parametric multivariate statistical comparison analysis is a very limited statistical tool (Johnson and Wichern, 2007; Tabachnick and Fidell, 2007; Hair et al., 2010). The more popular multivariate statistical comparison analysis is the Multivariate Analysis of Variance (i.e. MANOVA). It is used to measure the significant differences among more than two comparison groups towards more than one continuous targeted variable (Johnson and Wichern, 2007; Tabachnick and Fidell, 2007; Hair et al., 2010; Finch and French, 2013). In the context of Multivariate Analysis of Variance (i.e. MANOVA), the assumption of variance homogeneity across the groups is very important and is based on the Box's M test (Johnson and Wichern, 2007; Tabachnick and Fidell, 2007; Field, 2009; Hair et al., 2010; Finch and French, 2013). According to Tabachnick and Fidell (2007) and Field (2009), Box's M test is a very sensitive test and is robust when the sample size for each group is equal (Field, 2009). Therefore, the MANOVA test could always be used by researchers when the sample size for each of the comparison group is equal.

2.2 Bivariate and Multivariate Statistical Correlation Analysis

Initially, correlation analysis is the common method used to determine the significance of the bivariate relationship between two interested variables. Usually, Pearson' Correlation analysis is conducted when the assumptions of this test (i.e. normality distribution and both variables measurement at least at the interval level) are met (Field, 2009; Pallant, 2015; Bluman, 2012; Puth et al., 2013). This test is classified as the parametric statistical method. However, Spearman's Rank Correlation analysis is another common statistical correlation method that could be adopted if the assumptions of Pearson's Correlation analysis are not met (Field, 2009; Pallant, 2015).This test is categorized as non-parametric method (Wayne, 1990; Hauke and Kossowski, 2011).

On the other hand, if the researcher intends to examine causal and effect relationship, the multivariate statistical correlation analysis could be adopted. Usually, the causal and effect relationship involves a number of independent and dependent variables (Johnson and Wichern, 2007; Tabachnick and Fidell, 2007; Hair et al., 2010; Braun et al., 2014). Multiple Linear Regression analysis (i.e. MLR) is the appropriate method to be used if the set of independent variables is more than one variable paired with one continuous dependent variable (Montgomery et al., 2001; Kurtner et al., 2008; Field, 2009; Liebscher, 2012; Pallant, 2015). In addition, MLR could be used if the nature of the dependent variable measurement is at least at the interval level (Montgomery et al., 2001; Kurtner et al., 2008; Field, 2009; Pallant, 2015; Krzywinski and Altman, 2015). However, Logistic Regression analysis, Multinomial Regression analysis, or Discriminant Analysis are the preferred methods if the nature of dependent variable is a category variable (Johnson and Wichern, 2007; Tabachnick and Fidell, 2007; Field, 2009; Hair et al., 2010). In the context of Discriminant Analysis, it is conducted when the entire set of independent variables measurement is at least at the interval level (Johnson and Wichern, 2007; Tabachnick and Fidell, 2007; El-Sayed and Hamed, 2015), whereas Logistic Regression analysis or Multinomial Regression analysis are the statistical tools utilized if there exist a categorical variable in the set of independent variables (Johnson and Wichern, 2007; Field, 2009; Hair et al., 2010; Li et al., 2016), where this independent variable is treated as a dummy variable (Field, 2009).

In the event the researcher intends to examine the causal and effect relationship between a number of independent and dependent variables, the Structural Equation Modelling (i.e. SEM) is the best method to be used (Byrne, 2010; Hair et al., 2010; Hair et al., 2014; Fan et al., 2016). This statistical analysis allows the researcher to test the causal and effect relationship of those variables simultaneously (Byrne, 2010; Hair et al., 2010; Hair et al., 2014; Elsenhauer et al., 2015), thereby reducing the impact of Type 1 error (Byrne, 2010; Hair et al., 2010; Hair et al., 2014). There are two common theories under SEM statistical analysis. They are Covariance based SEM (i.e. CB-SEM) and Variance based SEM (i.e. VB-SEM) (Hair et al., 2014; Lowry & Gaskin, 2014; Richter et al., 2016; Sarstedt et al., 2016). CB-SEM technique is primarily for confirming or rejecting theories through hypothesis testing (Byrne, 2010; Hair et al., 2010). This technique is practical when the sample size is large, and the data is approximately normally distributed (Byrne, 2010; Hair et al., 2010). Most importantly, the model of the causal and effect relationship must be correctly specified (Byrne, 2010; Hair et al., 2010). The second technique in the SEM family, which is VB-SEM, is more robust towards the assumption of normality distribution and the sample size, and is used when the correct model of the causal and effect relationship cannot be ensured (Hair et al., 2011; Ringle et al., 2013; Hair et al., 2014; Dijkstra and Henseler, 2015). In addition, the VB-SEM technique is found to be most suitable for exploring the relationship among the variables (Hair et al., 2011; Ringle et al., 2013; Hair et al., 2014; Braojos-Gomez et al., 2015).

Despite the differences, both techniques share some common analogies in measuring the validity of the variable items (Hair et al., 2011; Ringle et al., 2013; Hair et al., 2014; Kaufmann and Gaeckler, 2015). Basically, both techniques use convergent validity and discriminant validity for accessing the goodness or the validity of the items to be measured (Hair et al., 2011; Ringle et al., 2013; Hair et al., 2014; Willaby et al., 2015). Assessment of factor loading (i.e. practically must be greater than .70), Average Variance Explained (i.e. practically must be greater than .50), and the Composite Reliability (i.e. practically must be greater than .70) are the common assessments for measuring the convergent validity for CB-SEM and VB-SEM (Byrne, 2010; Hair et al., 2010; Hair et al., 2011; Ringle et al., 2013; Hair et al., 2014). Apart from that, the Fornell-Larcker Discriminant analysis is another tool for accessing the discriminant validity for CB-SEM and VB-SEM (Byrne, 2010; Hair et al., 2010; Hair et al., 2011; Ringle et al., 2013; Hair et al., 2014). However, in measuring the significance of the causal and effect relationship among the variables, the CB-SEM analysis uses the Maximum Likelihood (i.e. ML) estimation technique (Byrne, 2010; Hair et al., 2010) whereas in the case of the VB-SEM analysis, the Ordinary Least Square (i.e. OLS) regression based estimation technique is used (Hair et al., 2011; Ringle et al., 2013; Hair et al., 2014).

The Exploratory Factor analysis (i.e. EFA) is one of the multivariate statistical correlation analyses that could be used to examine the validity of variable items. This EFA technique is employed to determine the number of variables underlying one general variable (Johnson and Wichern, 2007; Tabachnick and Fidell, 2007; Hair et al., 2010; Kim et al., 2016; Copenhaver et al., 2016). It is a statistical tool to be used for refinement or reconstruction or confirmation of the variables' structures that share a common variance (Field, 2009; Sakaluk and Short, 2016). Typically, EFA analysis is based on correlation matrix among the variable items (Johnson and Wichern, 2007; Tabachnick and Fidell, 2007; Hair et al., 2010; Ichikawa, 2015). Therefore, the variable items' measurement should be at least at the interval level (Johnson and

Wichern, 2007; Tabachnick and Fidell, 2007; Hair et al., 2010). Besides that, the considerations of sample size and normality distribution are also pre-requisites for performing this analysis (Tabachnick and Fidell, 2007; Field, 2009; Hair et al., 2010).

3.0 COMMON STATISTICAL SOFTWARE

Several statistical software are available for performing statistical analysis, namely Statistical Package for Social Sciences (i.e. SPSS), Minitab, SAS, R-programming, STATA, SEM-AMOS, SEM-SmartPLS, and WarpPLS. The most popular softwares for SEM are Analysis of Moments Structure (AMOS), Partial Least Square (PLS), LISREL, SEPATH, PRELIS, SIMPLIS, MPLUS, EQS and SAS (Hair et al., 2011; Zainudin, 2012a, 2012b). In general, there are two types of SEM (Lowry & Gaskin, 2014): Variance-based SEM, such as PLS and Co-variance based SEM, such as AMOS, Lisrel, EQS, MPlus. However, this paper only focuses on three statistical software packages commonly used in social sciences research, which are SPSS, AMOS and SmartPLS.

3.1 Statistical Package for Social Sciences (i.e. SPSS)

SPSS is a statistical package designed by the IBM Corporation and widely used by researchers or academicians worldwide. This statistical package is very user friendly and various statistical tests could be conducted using this software. This statistical software undertakes both comparison and correlational statistical tests in the context of univariate, bivariate and multivariate analysis for both the parametric and non-parametric statistical techniques.

3.2 SmartPLS

SmartPLS is a statistical package primarily designed by a team of software developers from the academia in Germany (Ringle et al., 2015). This statistical software undertakes SEM analysis using the Ordinary Least Square estimation techniques (Hair et al., 2011; Ringle et al., 2013; Hair et al., 2014), and is widely used by researchers exploring the theories.

3.3 AMOS

AMOS is a statistical package also designed by the team at IBM Corporation. AMOS software is widely used to confirm a theory, since it uses the ML estimation techniques in the SEM analysis (Byrne, 2010; Hair et al., 2010). Besides that, AMOS software is automatically available when the researcher purchases the SPSS software version 20.0 and above.

4.0 CHOOSING THE RIGHT STATISTICAL SOFTWARE FOR DATA ANALYSIS

In choosing the right statistical software for performing the data analysis, firstly, researchers usually look at their research objective. If the research objective is comparison analysis, usually SPSS statistical software is the preferred statistical package compared to other statistical packages such as MINITAB, STATA, and R-Programming statistical software. This is because the SPSS statistical software is easily able to perform both parametric and non-parametric comparison analysis. It also permits the researcher to check the assumptions of the tests, such as the normality test and outliers test. Besides that, this statistical package enables a frequency analysis to be perfectly conducted.

On the other hand, in the context of validating the variable items, if the researcher intends to refine the variable items using the EFA analysis, the SPSS statistical package is an appropriate statistical package, since it provides comprehensive output compared to other statistical software. The software also performs

EFA analysis by using a number of extraction estimation techniques such as Principal Component extraction technique, Principal Axis Factoring extraction technique and Maximum Likelihood estimation technique.

With respect to correlation analysis objectives, the SPSS statistical software could easily perform the Pearson's Correlation or Spearman's Rank Correlation tests for examining the bivariate relationship between two targeted variables. It could be used to carry out the MLR analysis with the organized output of regression analysis. In terms of categorical type of dependent variable, the researcher usually has a choice of either to perform Logistic Regression analysis, or Multinomial Regression analysis or Discriminant analysis. Therefore, SPSS statistical software is considered as an optimal statistical tool for performing these three types of statistical analysis.

However, if the researcher intends to examine causal and effect relationship between a number of independent and dependent variables, SEM analysis is the preferred statistical tool. Of late, SEM is becoming a popular method of analysis for studying relationships among constructs. SEM has the statistical ability to test the causal relationships between constructs with multiple measurement items (Hair, Ringle, & Sarstedt, 2011; Hair, Sarstedt, Pieper, & Ringle, 2012; Lowry & Gaskin, 2014; Noorazah & Juhana, 2012). SEM is an useful statistical tool for testing theories and conceptual models of the study empirically (Hair et al., 2011; Hair et al., 2012). Using SEM allows the researcher to determine whether the relationship among the constructs in the research framework is significant, based on the data gathered. SEM is a second-generation of multivariate analysis techniques which combines various techniques available in the first-generation of multivariate analysis (or known as OLS – Ordinary Least Squares), such as factor analysis (FA), regression and correlation (Hair et al., 2012; Lowry & Gaskin, 2014; Zainudin, 2012b).

PLS-SEM is used for data analysis to test the measurements and substantive models of the study and examine the relationships among constructs in the proposed research model. The proposed model is the nascent theoretical development derived from several theories. Thus, the prediction between constructs in the proposed model requires usage of PLS-SEM (Hair et al., 2011; Hair et al., 2012). PLS-SEM is very powerful to test the theory as compared to CB based SEM (Lowry & Gaskin, 2014). Furthermore, PLS-SEM is also employed as the complex research model is handled in a more effective and efficient manner, and it requires no GOF (goodness of fit) model which is central in CB-SEM. PLS-SEM is also frequently used in exploratory studies. Further, PLS SEM offers flexibility in terms of data analysis as it has the ability to process different types of nominal, ordinal, interval and ratio data (Hair et al., 2011; Hair et al., 2012). Moreover, the current research trends are also moving towards using PLS-SEM as a software to analyse quantitative data (Henseler, Ringle, & Sarstedt, 2015). The other advantages of using PLS-SEM, as outlined by Hair et al. (2011) and Hair et al. (2012), are the restrictive assumptions of the CB-SEM (co-variance based SEM), that is, the normality assumption is not met, the sample size is small, some of the variables are formative measures, and the focus of the study is on prediction and theoretical development. Hair et.al also maintained that although PLS-SEM operates using a small sample size, it is preferable to use a larger sample size to represent the population and yield more accurate results of model estimation. Another salient advantage of PLS-SEM is that, it is able to normalise the data for further analysis.

In general, there are several reasons why SEM PLS is used for data analysis. Among others, PLS-SEM is suitable for theory testing, it is more robust than traditional SPSS, it allows researchers to test all variables simultaneously, and the sample is more flexible as it does not require normality assumptions to be fulfilled and it works well with small sample size. Although some scholars argue that PLS-SEM is less rigourous, its usage has gained popularity, especially in business research. This is due to the unique features of PLS-SEM, namely PLS ability to handle smaller sample size as well as producing more robust and accurate results than CB-SEM if the assumptions of CB-SEM are not met. It is also a preferred statistical method if the nature of the research is more predictive than a confirmatory kind of study (Hair et al., 2011). Though the small sample size in PLS-SEM is said to have biasness against consistency, however differences in estimation results between the two are very minimal. If the sample sizes are bigger, then the results produced by PLS-SEM are similar to the results produced by CB-SEM (Lowry & Gaskin, 2014). Besides that, both statistical software for conducting the SEM analysis (i.e. AMOS and SmartPLS) have user friendly features and the outputs are clearly presented. The key distinctive features between CB-SEM and PLS-SEM, as highlighted by Hair et al. (2011) and Hair et al. (2012), are shown in **Error! Reference source not found.** below.

Table 1: Key Features of CB-SEM and PLS-SEM

CB-SEM	PLS-SEM
• Theory testing and confirmation	• Theory prediction and development
• Requires large sample size	• Able to operate with small sample size
• Normality assumptions must be met (restrictive assumptions)	• Normality assumptions need not be met (less restrictive assumptions)
• Data are continuous (reflective)	• Data could be formative
• Confimatory study	• Exploratory study

Source: Hair et al. (2011) ; Hair et al. (2012)

In addition to the above, PLS-SEM allows for more complex analysis for modeling latent variables, testing the indirect effect, multiple moderation effects and assessing the goodness of the proposed model (Lowry & Gaskin, 2014). Table 2 below summarises the statistical software and statistical analysis commonly used in the Social Science research field.

Table 2: Common Statistical Analysis Used in the Social Science Research Field

Research Objective	Type of Statistical Theory	Possible Method	Suggested Statistical Software
To examine the significant differences between two interested groups towards one continuous targeted variable	Univariate Comparison analysis	Independent t-test analysis	SPSS
		Mann-Whitney test analysis	SPSS
To measure the significant differences among more than two comparison groups towards one continuous targeted variable	Univariate Comparison analysis	One-way Analysis of Variance test (i.e. ANOVA) analysis	SPSS
		Kruskal-Wallis test analysis	SPSS
To measure the significant differences among more than two comparison groups towards more than one continuous targeted variable	Multivariate Comparison analysis	Multivariate Analysis of Variance test (i.e. MANOVA) analysis	SPSS

To determine the significant bivariate relationship between two continuous interested variables	Univariate Correlation analysis	Pearson' Correlation analysis	SPSS
		Spearman's Rank Correlation analysis	SPSS
To examine causal and effect relationship between a set of independent variables paired with one continuous dependent variable	Multivariate Correlation analysis	Multiple Linear Regression (i.e. MLR) analysis	SPSS
To examine causal and effect relationship between a set of independent variables, where these set of independent variables involve a categorical variable paired with one categorical dependent variable	Multivariate Correlation analysis	Logistic Regression analysis[a] or Multinomial Regression analysis[b]	SPSS
To examine causal and effect relationship between a set of independent variables, where these set of independent variables do not involve a categorical variable paired with one categorical dependent variable	Multivariate Correlation analysis	Discriminant analysis	SPSS
To examine causal and effect relationship between a number of independent and dependent variables with priority to confirming or rejecting the theories	Multivariate Correlation analysis	Covariance based Structural Equation Modelling (i.e. CB-SEM) analysis	AMOS
To examine causal and effect relationship between a number of independent and dependent variables with priority to exploring the theories	Multivariate Correlation analysis	Variance based Structural Equation Modelling (i.e. VB-SEM) analysis	SmartPLS
To refinement or reconstruct or confirm the variables' structure that share a common variance	Multivariate Correlation analysis	Exploratory Factor Analysis (i.e. EFA)	SPSS

Note: [a]*This analysis can be used if the dependent variable constitutes two categories.*
[b]*This analysis can be used if the dependent variable constitutes more than two categories.*

5.0 CONCLUSION

This paper aims to provide practical guidelines that could assist Social Sciences researchers choose the best statistical software to conduct effective statistical testing for their research. In conducting statistical testing, the researcher normally uses at least two types of statistical software for a complete procedure of statistical analysis. For example, when the researcher intends to conduct the preliminary data analysis (i.e. checking the missing values, checking the data distributions, etc.) the general statistical tools such as SPSS are considered a good choice. The researcher could further decide either to use AMOS or SmartPLS statistical software for testing their research hypothesis, as majority of Social Sciences researchers currently are keen to examine the causal and effect relationship between a number of independent and dependent variables in one theory. Nevertheless, it is very important to note that the selection of the best statistical software and appropriate statistical analysis is dependent very much on the research objectives and the research questions developed by the researchers. This is a prerequisite for any statistical analysis to be employed. Choosing the right statistical analysis helps researchers to derive accurate as well as robust results in order to explain the achievement of intended research objectives.

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