Why Apply SPSS, SmartPLS and AMOS: An Essential Quantitative Data Analysis Tool for Business and Social Science Research Investigations

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ABSTRACT

In the realm of business and social science research, selecting the right quantitative data analysis tool is pivotal for deriving actionable insights and validating hypotheses. This study were used a qualitative comparison and contrast methodology. The objective is to highlight the benefits of each tool and its appropriate uses in social science and commercial research. SPSS, SmartPLS, and AMOS are three prominent tools each offering distinct advantages tailored to various research needs. SPSS (Statistical Package for the Social Sciences) is widely recognized for its comprehensive range of statistical procedures and user-friendly interface, making it ideal for performing detailed descriptive and inferential analyses. SmartPLS (Partial Least Squares Structural Equation Modeling) specializes in variance-based SEM, providing robust capabilities for exploratory research and predictive modeling with complex datasets. Its focus on prediction and theory development is particularly beneficial for handling large and intricate models. AMOS (Analysis of Moment Structures), on the other hand, excels in covariance-based SEM, offering extensive tools for confirmatory factor analysis and structural modeling. Its graphical interface and model fit indices facilitate detailed model validation and hypothesis testing. Each software has its strengths and limitations, making them essential tools for addressing different aspects of quantitative research. Understanding their unique capabilities allows researchers to select the most appropriate tool for their specific analytical requirements.

Keywords: SPSS, SmartPLS, AMOS, Business and Social Science Research, Quantitative Data Analysis

INTRODUCTION

In the realms of business and social science research, quantitative data analysis plays a crucial role in uncovering insights, testing theories, and informing decision-making. To navigate the complexities of data and derive meaningful conclusions, researchers rely on advanced statistical tools. Among these, SPSS (Statistical Package for the Social Sciences), SmartPLS (Partial Least Squares), and AMOS (Analysis of

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Moment Structures) stand out as pivotal software solutions, each offering distinct functionalities suited to different analytical needs. Students and researchers in the domains of sociology, psychology, economics, business studies, medicine, engineering, and other disciplines are the main beneficiaries of this application. In addition, SPSS, SmartPLS, and AMOS are used by several public, corporate, and non-governmental organizations for a range of projects. For marketing and survey firms looking to forecast and analyze customer behavior, these data analysis tools are a great option (Vorhies, 2017). Each of these tools offers unique features suited to various research needs and methodologies. This study explores the significance of SPSS, SmartPLS, and AMOS in quantitative data analysis, their functionalities, and their applications in business and social science research.

METHODOLOGY OF THE STUDY

The relevance and use of three well-known quantitative data analysis tools SPSS (Statistical Package for the Social Sciences), SmartPLS (Partial Least Squares Structural Equation Modeling), and AMOS (Analysis of Moment Structures) are investigated in this study using a qualitative comparison and contrast methodology. The goal is to draw attention to each tool's advantages and suitable applications in business and social science research. With the integration of theoretical and practical viewpoints, this technique guarantees a methodical and comprehensive analysis of the instruments, offering an in-depth understanding of their research applications.

TYPES OF STATISTICAL ANALYSIS: UNIVARIATE, BIVARIATE, AND MULTIVARIATE

The most important tool for knowing and interpreting data is statistical analysis. It is divided into groups according to the quantity of variables and the complex nature of the correlations looked at. Univariate, bivariate, and multivariate analysis are the three main categories of statistical analysis. Analysis of a single variable to describe its properties and distribution is the main goal of univariate analysis. Measures of central tendency (mean, median, mode), dispersion (variance, standard deviation), and frequency distributions are among the fundamental understandings it offers of the data. Univariate analysis, for instance, can be used to characterize a population's wealth distribution or the average age of survey participants (Field, 2013).

The purpose of bivariate analysis is to determine how two variables interact with one another by analyzing their connection. It is employed to determine group differences, relationships, and causes. T-tests, cross-tabulations, and correlation coefficients are common techniques. For example, bivariate analysis can show if income level and educational achievement are significantly correlated (Cohen, Cohen, West, & Aiken, 2003; Sarker, B. K. et al., 2020).

In order to investigate intricate links and interactions, multivariate analysis entails the simultaneous examination of several variables. This kind of study is used to comprehend how various factors interact and influence the desired results. Factor analysis, cluster analysis, and multiple regression are among the techniques. When modeling complicated phenomena, such as forecasting consumer behavior based on several psychographic and demographic variables, multivariate analysis is essential (Hair, Black, Babin, Anderson, 2010). Therefore, univariate analysis offers a basic understanding of a single variable, bivariate research investigates the connections between two variables, and multivariate analysis examines complex links between many variables.

a. Comparison between Univariate and Multivariate Analysis:

Although they both serve different objectives and require different methods, univariate and multivariate analyses are crucial tools in statistical research. Researchers can select the best approach for their data analysis requirements by being aware of these distinctions.

Independent t-tests are frequently used in statistical comparison analysis to assess the significant differences between two interested groups with respect to a single targeted variable (Field, 2023; Pallant, 2024; Bluman, 2012; Kim, 2015). In the meanwhile, a common statistical technique for determining the statistically significant differences between more than two comparison groups with respect to a single target variable is the one-way ANOVA statistical tool (Field, 2013; Pallant, 2024; Bluman, 2012; Kim, 2015). Both tests' requirements, the targeted variable's distribution must be roughly normally distributed and its measurement must be at least at interval measurement. Therefore, both tests fall within the category of parametric statistical techniques. When the variables do not satisfy the assumption of normality and the desired measurement variable is of the nominal or ordinal kind, a non-parametric comparison analysis is typically conducted (Field, 2023; Pallant, 2024; Nahm, 2015; Sarker, B. K. et al., 2020). An alternate technique for analyzing differences between two interested groups about a single targeted variable is the Mann-Whitney comparison analysis, provided the assumptions of the independent t-tests were not satisfied. Moreover, in situations where the one-way ANOVA assumption cannot be satisfied, the Kruskall-Wallis comparison analysis test may be employed. The Kruskall-Wallis statistical test, however, is only carried out when the measurement of the targeted variables is at the ordinal level since the one-way ANOVA statistical test is resilient towards the assumption of normality distribution.

Researchers who aim to employ multivariate statistical comparison analysis must carefully prepare their study designs in order to apply this form of analysis. For this reason, non-parametric multivariate statistical comparison analysis is a statistical instrument with significant limitations. The Multivariate Analysis of Variance, or MANOVA, is the more often used multivariate statistical comparison analysis. Its purpose is to assess the statistically significant differences between two or more comparison groups with respect to several continuous targeted variables (Tabachnick and Fidell, 2007; Johnson and Wichern, 2007; Hair et al., 2010; Finch and French, 2013). The assumption of variance homogeneity across the groups is crucial when doing Multivariate Analysis of Variance, or MANOVA, and is based on the Box's M test. Box's M test is a highly sensitive test that is robust when the sample size for each group is identical, according to Tabachnick and Fidell (2007) and Field (2023). Thus, since the sample sizes for each comparison group are identical, researchers may always perform the MANOVA test.

b. Comparing Bivariate and Multivariate Correlation Analysis in Statistics

First, the most popular technique for figuring out how significant the bivariate link is between two variables of interest is correlation analysis. When the test's assumptions that is, the normality distribution and the measurement of both variables at least at the interval level are satisfied, Pearson's Correlation analysis is often carried out (Field, 2023; Pallant, 2024; Bluman, 2012; Puth et al., 2013). The parametric statistical approach is how this test is categorized. If the conditions of Pearson's Correlation analysis are not satisfied, however, another popular statistical correlation technique that may be used is Spearman's Rank Correlation analysis (Field, 2013; Pallant, 2015). Non-parametric methods include this test (Hauke and Kossowski, 2011).

However, multivariate statistical correlation analysis may be used if the researcher wants to look at the link between cause and effect. Numerous independent and dependent factors are often involved in the causation and effect connection (Johnson and Wichern, 2007; Tabachnick and Fidell, 2007; Hair et al., 2010; Braun et al., 2014). If the collection of independent variables consists of many variables coupled with a single continuous dependent variable, then multiple linear regression analysis, or MLR, is the right approach to utilize (Montgomery et al., 2001; Kurtner et al., 2008; Field, 2013; Liebscher, 2012; Pallant, 2015; Krzywinski and Altman, 2015). Furthermore, provided the dependent variable is measured at least at the interval level, MLR may be applied. However, if the dependent variable is a category variable, then the best approaches are Multinomial Regression Analysis, Logistic Regression Analysis, or Discriminant Analysis (Pervin, M. T. et al., 2020; Ghosh, S. K. et al., 2021). Whereas Multinomial Regression analysis or Logistic Regression analysis are the statistical tools used if there is a categorical variable in the set of independent variables (Johnson and Wichern, 2007; Field, 2013; Hair et al., 2010; Li et al., 2016; El-Sayed and Hamed, 2015; Pervin, M. T. et al., 2021; Sarker, B. P., 2023), where this independent variable is treated as a dummy variable. Discriminant analysis is conducted when the entire set of independent variables measurement is at least at the interval level.

Structural Equation Modelling, or SEM, is the most appropriate approach to apply if the researcher wants to investigate the causation and effect link between several independent and dependent variables (Byrne, 2024; Hair et al., 2010; Hair et al., 2014; Fan et al., 2016; Elsenhauer et al., 2015). The researcher can lessen the impact of Type-I mistake by testing the causation and effect relationship of those factors concurrently with the use of statistical analysis. When it comes to SEM statistical analysis, there are two popular hypotheses. According to Hair et al. (2014), Lowry & Gaskin (2014), Richter et al. (2016), and Sarstedt et al. (2016), they are Covariance based SEM (also known as CB-SEM) and Variance based SEM (also known as VB-SEM). The primary purpose of the CB-SEM approach is hypothesis testing, which is used to confirm or reject ideas. When the data is roughly normally distributed and the sample size is big, this strategy can be applied. Above all, it is crucial to accurately specify the model of the cause and effect connection. When it is not possible to determine which model best captures the causal and effect relationship, the second method in the SEM family (VB-SEM) is employed. It is more resilient to assumptions about sample size and normality distribution (Hair et al., 2011; Ringle et al., 2013; Hair et al., 2014; Dijkstra and Henseler, 2015; Braojos-Gomez et al., 2015). Furthermore, it is discovered that the best method for examining the association between the variables is the VB-SEM methodology.

In analyzing the validity of the variable items, both approaches have some similar parallels despite their differences (Hair et al., 2011; Ringle et al., 2013; Hair et al., 2014; Willaby et al., 2015; Kaufmann and Gaeckler, 2015). In essence, both methods access the validity or quality of the items to be tested by using discriminant validity and convergent validity. Common assessments used to measure the convergent validity for CB-SEM and VBSEM include factor loading (i.e., practically greater than 0.70), Average Variance Explained (i.e., practically greater than 0.50), and Composite Reliability (i.e. practically greater than 0.70). In addition, another method for determining the discriminant validity for VB-SEM and CBSEM is the Fornell-Larcker Discriminant analysis. However, the Maximum Likelihood (ML) estimation technique is used in the CBSEM analysis to measure the significance of the causal and effect relationship among the variables, whereas the Ordinary Least Square (OLS) regression based estimation technique is used in the VB-SEM analysis.

One multivariate statistical correlation study that may be used to assess the validity of variable items is the Exploratory Factor analysis, or EFA. To find how many variables there are underlying a single general variable, this EFA approach is used (Johnson and Wichern, 2007; Tabachnick and Fidell, 2007; Hair et al., 2010; Kim et al., 2016; Copenhaver et al., 2016; Ichikawa, 2015). It is a statistical technique that may be used to confirm, improve, or reconstruct the structures of the variables that have a similar variance. The correlation matrix between the variable items is usually the foundation for EFA analysis. For this reason, the measurement of the variable items must to be done at the very least at the interval level. In addition, the analysis cannot be performed without taking into account the normalcy distribution and sample size.

QUANTITATIVE DATA ANALYSIS AND THEIR APPLICATION OF STATISTICAL TOOLS:

Quantitative data analysis is the methodical study of numerical data with the goal of identifying trends, validating theories, and assisting in decision-making. In this procedure, statistical tools are essential because they offer the techniques required for data analysis, result interpretation, and conclusion making. Depending on the goals of the study, the kinds of data, and the analytical needs, these technologies are applied differently.

While multivariate analysis and structural equation modeling (SEM) tackle intricate interactions among variables, descriptive statistics provide fundamental insights while inferential statistics enable researchers to evaluate hypotheses and make predictions. Tools that address certain analytical demands include AMOS, SPSS, and PLS Path Modeling. The optimal use of these tools relies on the research questions, data characteristics, and objectives, enabling researchers to gain significant insights and make smart choices across many different fields.

MOST FREQUENTLY USED STATISTICAL APPLICATIONS:

The Statistical Package for Social Sciences (also known as SPSS), SEM-AMOS, SEM-SmartPLS, and WarpPLS are among the statistical software programs that may be used to do statistical analysis. The most widespread softwares for SEM include Analysis of Moments Structure (AMOS), Partial Least Square (PLS), LISREL, SEPATH, PRELIS, SIMPLIS, MPLUS, EQS and SAS (Hair et al., 2011; Zainudin, 2012a, 2012b; Sarker, B.K. et al., 2020). According to Lowry and Gaskin (2014), there are two main categories of SEM: variance-based SEM, like PLS, and co-variance-based SEM, like AMOS, Lisrel, EQS, and MPlus. Nevertheless, the three statistical software programs SPSS, AMOS, and SmartPLS which are often utilized in business and social science research are the only ones covered in this work.

a. Statistical Package for Social Sciences (SPSS):

SPSS is a versatile and widely used software developed by IBM, renowned for its comprehensive suite of statistical procedures and user-friendly interface. Its application spans from basic descriptive statistics to complex inferential techniques, making it invaluable for researchers across various disciplines. SPSS excels in data management, allowing researchers to handle large datasets, clean and transform data, and perform a wide range of statistical analyses including t-tests, ANOVA, regression, and factor analysis (Pervin, M.T. et al., 2020). Its intuitive graphical interface and extensive documentation make it accessible even to those with limited statistical backgrounds, thus facilitating a broad spectrum of quantitative research activities in both business and social sciences (Sarker, B.K. et al., 2020; Pervin, M.T. et al., 2020; Sarker, B. K. et al., 2023).

Benefits and Drawbacks of SPSS:

Benefits:

SPSS offers a graphical interface that simplifies data entry, manipulation, and analysis, making it accessible even for users with limited statistical expertise (Field, 2013). It includes a wide range of statistical techniques, from basic descriptive statistics to advanced multivariate analysis, facilitating various types of quantitative research (Sarker, B. K. et al., 2021; Pallant, 2024; Sarker, B.K. et al., 2020). It provides robust data management features, including data cleaning, transformation, and handling of missing values, which streamline the analytical process (IBM Corp., 2024). This analysis tools allows for extensive customization of tables, charts, and reports, aiding in the presentation of results tailored to specific needs (Field, 2013). SPSS comes with thorough documentation, tutorials, and support resources, which are valuable for troubleshooting and learning (Pallant, 2024).

Drawbacks:

SPSS can be expensive, with licensing fees that may be prohibitive for smaller organizations or individual users (IBM Corp., 2024). While it supports syntax scripting, SPSS is less flexible than programming languages like R or Python for complex custom analyses and automation (Field, 2013). SPSS is a proprietary software with limited compatibility and flexibility compared to open-source alternatives, potentially restricting users' ability to integrate with other tools (Pallant, 2024). SPSS can be resource-intensive, requiring significant computational power for large datasets and complex analyses, which might impact performance.

b. SmartPLS:

A group of German academic software developers created the statistical tool SmartPLS (Ringle et al., 2015). **SmartPLS** is a specialized software for Partial Least Squares Structural Equation Modeling (PLS-SEM), ideal for examining complex models with latent variables. PLS-SEM is particularly useful in exploratory research (Hair et al., 2011; Ringle et al., 2013; Hair et al., 2014) where theoretical frameworks are still evolving or where the data does not meet the stringent assumptions of traditional SEM. SmartPLS allows researchers to model complex relationships between variables and construct predictive models, making it a valuable tool in fields such as marketing, management, and social science. Its user-friendly graphical interface enables researchers to visually build path models, analyze relationships, and interpret results, facilitating an iterative approach to model development and refinement.

Benefits and Drawbacks of SmartPLS

Benefits:

SmartPLS uses Partial Least Squares Structural Equation Modeling (PLS-SEM), which is ideal for exploratory research and theory development when the data is complex and non-normally distributed (Hair et al., 2024). It handles various types of data and models, including formative and reflective constructs, and allows for the analysis of latent variables (Ringle, Sarstedt, & Straub, 2012). The software is user-friendly with a graphical interface that simplifies model specification and analysis (Hair et al., 2024). SmartPLS focuses on prediction and can handle large datasets and complex models with multiple constructs and indicators (Henseler, Ringle, & Sinkovics, 2009). It includes robust bootstrapping techniques for assessing the statistical significance of path coefficients and model parameters (Ringle et al., 2015). Unlike covariance-based SEM, PLS-SEM does not require data to follow a multivariate normal distribution, making it suitable for real-world data (Hair et al., 2024). Provides detailed reports and visualizations for model evaluation and result interpretation.

Drawbacks:

PLS-SEM models can become complex, making interpretation challenging, especially for those unfamiliar with the method (Hair et al., 2024). It is less effective for confirmatory research compared to covariance-based SEM, as it is more suited for exploratory analysis (Ringle et al., 2015). PLS-SEM can produce unreliable results with very small sample sizes (Hair et al., 2024). Unlike covariance-based SEM, PLS-SEM lacks conventional goodness-of-fit indices, which can be a limitation for model validation (Henseler et al., 2009). While SmartPLS offers various licensing options, costs can be a concern for some users.

c. AMOS

Another statistical program created by the IBM Corporation team is called AMOS. Because AMOS software employs ML estimating techniques in the SEM analysis, it is frequently used to verify theories (Byrne, 2024; Hair et al., 2010). **AMOS**, also developed by IBM, focuses on Structural Equation Modeling (SEM) and is known for its ability to handle intricate models involving multiple variables and relationships. SEM is a powerful technique for testing theoretical models and validating hypotheses about the relationships between latent constructs and observed indicators. AMOS provides a graphical modeling environment that simplifies the specification and modification of SEM models, allowing researchers to create path diagrams, assess model fit, and make necessary adjustments based on goodness-of-fit indices such as Chi-square, RMSEA, and CFI. This capability is particularly beneficial for theory-driven research in business and social sciences, where validating complex theoretical constructs and understanding structural relationships are critical.

Advantages and Disadvantages of AMOS

Advantages:

AMOS offers a graphical user interface that simplifies the construction of structural equation models (SEM) with drag-and-drop functionality, making it user-friendly for those with limited coding experience (Arbuckle, 2024; Byrne, 2024). It supports complex SEM analyses, including path analysis, confirmatory factor analysis, and latent variable modeling, providing robust tools for understanding variable relationships (Kline, 2024; Schumacker & Lomax, 2024). AMOS provides a range of fit indices (e.g., Chi-Square, CFI, RMSEA) to assess the adequacy of the model, helping users evaluate how well the model fits the data (Brown, 2024). It includes methods for handling missing data, such as Full Information Maximum Likelihood (FIML), enhancing the reliability of analyses (Little & Rubin, 2024; Arbuckle, 2023). AMOS allows detailed exploration of direct and indirect effects among variables, aiding in the identification of causal relationships (Byrne, 2024; Schumacker & Lomax, 2024).

Disadvantages:

As models increase in complexity, AMOS can become cumbersome, making model specification and interpretation more challenging (Kline, 2024; Brown, 2024). AMOS is a commercial software with licensing fees, which might be prohibitive for individual researchers or small institutions (Arbuckle, 2023; Byrne, 2024). AMOS lacks some advanced features found in other SEM software, such as Bayesian estimation or extensive model modification capabilities (Schumacker & Lomax, 2024). Unlike some alternative SEM tools, AMOS may not handle non-normal data distributions as effectively, potentially limiting its applicability for certain analyses (Kline, 2024; Little & Rubin, 2024).

SELECTING APPROPRIATE STATISTICAL SOFTWARE FOR ANALYSIS OF DATA

Selecting the appropriate statistical software for data analysis involves evaluating the specific analytical needs of a study and the features of available software. SPSS (Statistical Package for the Social Sciences), SmartPLS (Partial Least Squares Structural Equation Modeling), and AMOS (Analysis of Moment Structures) each offer distinct advantages and limitations that can influence their suitability for various research purposes. If the research objective is comparison analysis, usually SPSS statistical software is the preferred statistical package compared to other statistical packages such as SmartPLS, and AMOS 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, the SPSS statistics package is a suitable statistical package as it offers complete output in comparison to other statistical packages, if the researcher plans to improve the variable items utilizing the EFA analysis in the context of verifying the variable items. Additionally, the program functions. EFA analysis via the use of many extraction estimation approaches, including maximum likelihood estimation, principal component extraction, and principal axis factoring extraction.

The Pearson's Correlation or Spearman's Rank Correlation tests might be simply performed using the SPSS statistical software in order to examine the bivariate relationship between two targeted variables with respect to the objectives of correlation analysis. With the structured output from regression analysis, it might be utilized to do MLR analysis. The researcher often has three options when it comes to categorical dependent variables: discriminant analysis, multinomial regression analysis, and logistic regression analysis. Consequently, SPSS statistical software is thought to be the best statistical instrument for carrying out these three categories of statistical analysis.

SEM analysis, on the other hand, is the recommended statistical method if the researcher plans to investigate the cause and effect relationship between several independent and dependent variables. SEM is gaining popularity as an analytical technique these days for examining the correlations between components. Multiple measurement items can be used in SEM to statistically investigate the causal links between constructs (Hair, Ringle, & Sarstedt, 2011; Hair, Sarstedt, Pieper, & Ringle, 2012; Lowry & Gaskin, 2014; Noorazah & Juhana, 2012). SEM is a helpful statistical method for experimentally verifying the study's ideas and conceptual models (Hair et al., 2024; Hair et al., 2024). Based on the collected data, the researcher might use SEM to assess the significance of the link between the constructs in the study framework. Factor analysis (FA), regression, and correlation are examples of techniques available in the first generation of multivariate analysis (also known as OLS, or Ordinary Least Squares) that are combined in SEM, a second generation of multivariate analysis techniques.

PLS-SEM is utilized in data analysis to investigate the links between the components in the suggested research model and test the study's measurements and substantive models. The suggested model is a work in progress that draws from other hypotheses. Accordingly, PLS-SEM must be used for the prediction between the model's constructs (Hair et al., 2011; Hair et al., 2024). Compared to CB-based SEM, PLS-SEM is far more effective in testing the theory (Lowry & Gaskin, 2014). Additionally, PLS-SEM is used because it handles complicated research models more effectively and efficiently and doesn't require the GOF (goodness of fit) model, which is essential to CB-SEM. Exploratory investigations also commonly employ PLS-SEM. Furthermore, because PLS SEM can handle various kinds of nominal, ordinal, interval, and ratio data, it provides versatility in terms of data analysis. Furthermore, PLS-SEM is increasingly being used as a program in research to analyze quantitative data (Henseler, Ringle, & Sarstedt, 2015). According to Hair et al. (2011) and Hair et al. (2019), there are additional benefits to utilizing PLS-SEM, such as avoiding the restrictive assumptions of CB-SEM (co-variance based SEM), which include the following: the sample size is small, some of the variables are formative measures, the study is focused on prediction and theoretical development, and the normality assumption is not met. Hair et al. also argued that while PLS-SEM need small sample sizes to function, bigger sample sizes are better for representing the population and producing more accurate model estimate results. The ability of PLS-SEM to normalize the data for further analysis is another noteworthy benefit.

SEM PLS is generally employed for data analysis for a number of reasons. PLS-SEM has several advantages than regular SPSS, including being more robust, allowing researchers to test all variables at once, and having a more flexible sample due to its ability to operate with small sample sizes and lack of normality assumptions. It is well suited for theory testing. PLS-SEM has become more widely used, particularly in business research, despite the claims of some academics that it is less rigorous. This is because PLS-SEM has several advantages to CB-SEM, such as the latter's inability to handle lower sample sizes and its capacity to provide more reliable and accurate findings when its presumptions are not satisfied. According to Hair et al. (2011), this statistical strategy is also favored when the research is more predictive in nature rather than confirmatory. Although it is claimed that PLS-SEM's limited sample size introduces bias against consistency, there are very little variations in the estimation outcomes between the two. Larger sample sizes lead to findings using PLSSEM that are comparable to those from CB-SEM (Lowry & Gaskin, 2014). Aside from that, the results of the SEM analysis are displayed in an understandable manner using both of the statistical programs, AMOS and SmartPLS.

CONCLUSIONS

In contemporary research across business and social sciences, selecting the right quantitative data analysis tool is crucial for deriving meaningful insights and making informed decisions. SPSS, SmartPLS, and AMOS each offer unique strengths that cater to different analytical needs, making them essential tools in the research toolkit. SPSS is renowned for its extensive range of statistical procedures and user-friendly interface, which facilitates comprehensive data management and analysis (Field, 2023; Pallant, 2024). It excels in conducting basic and advanced statistical tests, making it ideal for descriptive and inferential analyses across various research fields (IBM Corp., 2024). However, martPLS provides robust capabilities for Partial Least Squares Structural Equation Modeling (PLS-SEM), which is particularly valuable for exploratory research and predictive modeling (Hair et al., 2024; Ringle et al., 2024). It is suited for handling complex models and large datasets, focusing on theory development and predictive accuracy (Henseler et al., 2024). Furthermore, AMOS, with its emphasis on covariance-based SEM, is a powerful tool for confirmatory factor analysis and structural modeling (Arbuckle, 2024; Byrne, 2024). Its graphical interface and comprehensive fit indices facilitate detailed model validation and hypothesis testing (Kline, 2024; Schumacker & Lomax, 2024). In conclusion, the choice between SPSS, SmartPLS, and AMOS depends on the research objectives and data characteristics. SPSS is ideal for general statistical analysis, SmartPLS for exploratory and predictive modeling, and AMOS for confirmatory SEM. Each tool's unique features make them indispensable for addressing different aspects of quantitative research, enabling researchers to tailor their approach to meet specific analytical needs (Field, 2023; Hair et al., 2024; Arbuckle, 2024).

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