A comparative analysis of multivariate approaches for data analysis in management sciences

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Abstract: *The researchers use the SEM-based multivariate approach to analyze the data in different fields, including management sciences and economics. Partial least square structural equation modeling (PLS-SEM) and covariance-based structural equation modeling (CB-SEM) are powerful data analysis techniques. This paper aims to compare both models, their efficiencies and deficiencies, methodologies, procedures, and how to employ the models. The outcomes of this paper exhibited that the PLS-SEM is a technique that combines the strengths of structural equation modeling and partial least squares. It is imperative to know that the PLS-SEM is a powerful technique that can handle measurement error at the highest levels, trim and unbalanced datasets, and latent variables. It is beneficial for analyzing relationships among latent constructs that may not be candidly witnessed and might not be applied in situations where traditional SEM would be infeasible. However, the CB-SEM approach is a procedure that pools the strengths of both structural equation modeling and confirmatory factor analysis. The CB-SEM is a dominant multivariate technique that can grip multiple groups and indicators; it is beneficial for analyzing relationships among latent variables and multiple manifest variables, which can be directly observed. The paper concluded that the PLS-SEM is a more suitable technique for analyzing relations among latent constructs, generally for a small dataset, and the measurement error is high. However, the CB-SEM is suitable for analyzing compound latent and manifest constructs, mainly when the goal is to generalize results to specific population subgroups. The PLS-SEM and CB-SEM have specific efficiencies and deficiencies that determine which technique to use depending on resource availability, the research question, the dataset, and the available time.*

Keywords: *Partial least square-SEM (PLS-SEM), covariance-based-SEM (CB-SEM), SEM-based multivariate approach, multiple manifest variables, PLS-SEM vs. CB-SEM modeling.*

JEL Classification: *C8, C42, C52.*

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Introduction

The researchers use covariance-based structural equation modeling (CB-SEM) and partial least square structural equation modeling (CB-SEM) to analyze the data of complicated connections among the latent and manifest constructs (Ahmed et al., 2021; Hair et al., 2022). Still, there are some vital differences between the two multivariate techniques; for example, PLS-SEM and CB-SEM modeling handle collinearity differently (Ahmed et al., 2022; Hair et al., 2019; Sarstedt et al., 2019). However, the PLS-SEM is very beneficial for managing data with a high degree of collinearity because it divides the data into latent variables uncorrelated using the PLS-SEM method (Sarstedt et al., 2022). On the other hand, the CB-SEM modeling is founded on multivariate normality and necessitates the data to be uncorrelated, as highlighted by Lu et al. (2020) and Hair Jr. et al. (2017). When the data is highly correlated, CB-SEM may generate unreliable or inconsistent results (Becker et al., 2022; Legate et al., 2022). Another difference is how the models are estimated, as Sarstedt et al. (2019) demonstrate. The PLS-SEM modeling uses a technique called bootstrapping to estimate the model parameters. This method can be computationally intensive but allows for a trustworthy approximation of factors in the presence of outliers and non-normality. The CB-SEM uses maximum likelihood approximation, which is computationally efficient but may not work well with non-normal data or outliers, according to Hair Jr. et al. (2017) and Mueller and Hancock (2018). The CB-SEM bases its assumptions on the multivariate normality hypothesis and demands that the data be uncorrelated (Ahmed et al., 2021; Hair et al., 2019; Hayes et al., 2017). For handling data with non-normality, outliers, and missing values, the PLS-SEM is not based on distributional assumptions and is, therefore, more flexible (Ringle et al., 2022; Sarstedt & Cheah, 2019). In light of this, it has been proven by Hwang et al. (2020), Ringle et al. (2015), and Hair et al. (2018) that PLS-SEM is a more reliable and adaptable method for assessing complex and correlated data than CB-SEM, which is based on multivariate normality assumptions. However, the technique chosen depends on the goals, research questions, and dataset characteristics (Hair et al., 2022). The CB-SEM and PLS-SEM are multivariate methodologies, but each has strengths and weaknesses.

The PLS-SEM is a statistical technique that combines the benefits of structural equation modeling partial and least squares to evaluate complex associations between latent variables and observable datasets, as highlighted by Sarstedt et al. (2019), and Ahmed et al. (2022). The PLS-SEM is particularly helpful in handling data with a high degree of collinearity since it uses the PLS-SEM technique to break the dataset down into uncorrelated latent variables. The PLS-SEM employs a more suitable parameter estimation technique for examining the model's parameters in the presence of outliers and non-normality (Memon et al., 2019). PLS-SEM has excellent flexibility because it does not rely on distributional assumptions and can handle data with non-normality, outliers, and missing values, according to Hair et al. (2010) and Sarstedt et al. (2021). The PLS-SEM technique can estimate latent variables that symbolize unobserved or underlying constructs in the data (Hair & Sarstedt, 2021; Legate et al., 2022). The PLS-SEM technique permits the study of numerous groups/subpopulations in the data, which can help compare groups or measurement invariance tests. According to Sarstedt et al. (2019) claim, the PLS-SEM can also handle correlations between constructs that are not linear. The PLS-SEM enables an understanding of the interactions between constructs by providing details on the intensity and direction of the associations and the comparative significance of each construct in the considered model (Legate et al., 2022). The PLS-SEM analysis can be performed using various programs, including the Smart-PLS, Warp-PLS, XLSTAT, and R packages for PLS-SEM (Memon et al., 2019; Parmar et al., 2022). Hence, it can be supposed that the PLS-SEM is an effective technique for evaluating complex, highly connected data since it enables the modeling and handling of non-linear relationships in a robust, flexible, and understandable manner (Hair et al., 2014; Hair et al., 2019).

The CB-SEM is used by Hayes et al. (2017) and Lu et al. (2020) to examine a complicated relationship between latent constructs and observable data. The CB-SEM uses maximum likelihood approximation to estimate the model parameters, which is computationally efficient as one of its essential characteristics (Ahmed et al., 2022; Hooper et al., 2008). Given that the CB-SEM technique is founded on the assumptions of multivariate normality, an uncorrelated dataset is needed (Hair et al., 2018). Latent variables, or unseen or underlying constructs in the data, can be estimated using CB-SEM (Hair et al., 2011; Hooper et al., 2008). The CB-SEM offers many fit indices that could be employed to examine the model fit and spot any potential issues under consideration (Bentler, 1990). Several groups or subpopulations can be analyzed using CB-SEM, allowing for comparing groups or testing invariance measurements (Sarstedt et al., 2021). According to Sarstedt et al. (2019) and Rigdon (2016), the CB-SEM enables model adjustment by introducing or eliminating latent structures or routes. Various softwares are available for CB-SEM analysis, including AMOS, LISREL, and M-Plus (Becker et al., 2022; Hair et al., 2018). By providing details on the strength and direction of the link and the relative prominence of each construct in the model under consideration, CB-SEM enables the analysis of relationships between variables (Parmar et al., 2022). Thus, it is debated that CB-SEM is a statistical methodology using the computationally effective maximum likelihood method to examine the model's parameters. It is predicated on multivariate normalcy and necessitates the absence of correlation in the data. Additionally, it offers many goodness-of-fit statistics, allows for model adjustment and estimation of latent variables, and makes software available (Hair et al., 2014).

This paper's goal is to assess and contrast PLS-SEM vs. CB-SEM modeling. This study may be helpful to future researchers, who may use it to decide which approach to use under particular circumstances. The CB-SEM and PLS-SEM multivariate approaches are also covered comprehensively in this study. The CB-SEM and PLS-SEM multivariate approaches have also been described in earlier research, but that literature does not discuss every aspect of both multivariate techniques (Becker et al., 2022; Hair et al., 2019; Legate et al., 2022; Ringle et al., 2022), and several other studies, which had several drawbacks. Previous literature, for instance, does not address several features, such as sample size, multicollinearity issues, components, types of CB-SEM and PLS-SEM, model fit indices, measurement, and structural models. The current study provides an in-depth analysis of the CB-SEM and PLS-SEM multivariate techniques' features, benefits, shortcomings, and methodology.

The remaining sections of the paper are divided into numerous sections, such as section 2 (Theoretical Background), section 3 (Research methodology), section 4 (Results and discussion), section 5 (Conclusions), and Limitations and future research orientations.

1. Theoretical background

Previous literature has explored the difference between PLS-SEM and CB-SEM modeling. The literature differentiated their categories and demonstrated the efficiencies and deficiencies of both models (Hair et al., 2006; Hair & Sarstedt, 2021). Several studies have demonstrated that PLS-SEM is an SEM to explore complex relationships between numerous parameters (Hair et al., 2022; Henseler et al., 2015). Similarly, previous literature exhibited that CB-SEM models could be used depending on the research goals, research questions, and data arrangements. PLS-PM (PLS path modeling) is a PLS-SEM variant used to evaluate associations between observed and unobserved elements in the model and to estimate the path coefficients connecting these variables. PLS-SEM and CB-SEM modeling come in a multiplicity of different forms (Memon et al., 2019; Ringle et al., 2015). According to Hair et al. (2022) and Sarstedt and Cheah (2019), PLS-CFA (PLS-confirmatory factor analysis) is used to gauge theories about the structure of the measurement model, including theories about the number of components, factor loadings, and measurement errors. The PLS-SEM is a method to estimate the path coefficients between constructs and investigate associations between unobserved elements in a model (Ringle et al., 2022). PLS-regression is accustomed to evaluating the association among predetermined predictors of a construct of interest, such as a dependent variable (Hair & Sarstedt, 2021; Legate et al., 2022). By identifying the linear blend of components that maximizes the covariance among constructs, PLS-canonical analysis is used to categorize the underlying structure of a dataset, as demonstrated by Richter et al. (2020) and Hair et al. (2017). A set of data is divided into groups using PLS-DA (PLS-discriminant analysis), a kind of PLS-SEM grounded on the values of predictors (Hair et al., 2022). PLS-SEM with small data is the type of PLS-SEM that is very helpful when several constructs are more incredibly associated with a small sample size; missing data, non-normality, and multicollinearity can all be accommodated by it (Matthews, 2017; Ringle et al., 2015).

According to previous studies, there are other varieties of CB-SEM modeling, including confirmatory factor analysis, a sort of CB-SEM accustomed to testing a considered measurement model based on fixed latent variables and preset manifest factors (Ahmed et al., 2022; Hair et al., 2022). It could support or disprove a scale's or measure's factor structure (Hair et al., 2010; Hussain & Ahmed, 2020). Path analysis assesses the direction, strength, and correlation between various parameters. It can evaluate theories of causal relationships between many components (Hayes et al., 2017). This kind of CB-SEM, known as latent growth curve modeling (LGCM), looks at how variables change over time. Examining a variable's rate of change and its consistency across time is a common practice (Hair et al., 2011). Grounded on the provisions of answers to a set of observed factors, latent class analysis (LCA) is frequently used to ascertain subdivisions or classes within a population (Nunkoo et al., 2020). The CB-SEM method, known as multigroup SEM, compares an association among constructs across various groups or populations. It can be used to look for variations or patterns in the relationships between variables between various groups (Cohen, 1992; Hayes et al., 2017). This kind of CB-SEM, SEM with missing data, deals with missing data in the analysis. It is customary to look at the parameters of the model and missing data simultaneously (Hair et al., 2006). SEM without normality data is the type of CB-SEM that works with non-normal data for the analysis. Using reliable estimating approaches, the model's parameters could be evaluated (Henseler et al., 2015).

According to Ringle et al. (2015) and Hair et al. (2010), the sample size for PLS-SEM should be sizable to ensure adequate power for the statistical analysis and to obtain a suitable level of generalizability (Hair et al., 2010; Ringle et al., 2015). However, PLS-SEM sample size recommendations are less accurate than those for traditional SEM (Sharma et al., 2021). PLS-SEM is considered a more reliable method than traditional SEM regarding sample size and measurement error because it can tolerate higher levels of measurement error (Ahmed et al., 2019; Hair et al., 2019). As a result, PLS-SEM frequently has more flexible sample size requirements than typical SEM. It is vital to keep in mind that sample size is always determined by the study purpose, the resources available, and the amount of time available, even if some studies have shown that PLS-SEM may be employed with datasets as low as 50–100 instances (Hayes et al., 2017).

Previous literature also discussed the required sample for PLS-SEM modeling; according to Hussain and Ahmed (2020), Hussain et al. (2021), and Zaidi et al. (2022), the sample size required to achieve a specific power level, for instance, 80% or 90%, can be determined in various ways, including simulation studies and power analysis techniques. The sample size is calculated considering the research topic, the resources available, and the amount of time available. It is crucial to remember that sample size estimations are frequently approximate. It is also critical to remember that the PLS-SEM sample size requirements vary depending on the number of predictors and model complexity (Sarstedt & Cheah, 2019). As models become more complicated, sample sizes become more critical. The sample size must be proficient at ensuring the accuracy and objectivity of the estimated values (Shmueli et al., 2019). Similarly, previous literature also discussed that the sample size is a vital concern in the CB-SEM technique since it can affect the valuation of the considered model's parameters and the model's capacity to fix the dataset. A larger sample size will produce more precise parameter estimates and a better model-data fit (Hair et al., 2014; Sharma et al., 2021).

According to Hair et al. (2011), the optimal sample size will depend on the complexity of the model, the number of indicators, the latent factors quantity, and the level of measurement error. There are numerous methods for computing the sample size for the CB-SEM. The recommendations for the sample size for the CB-SEM depend on various aspects, among them the number of factors, the number of estimated parameters, and the amount of measurement error (Hair et al., 2011). One of several recommended sample size criteria is the "10:1 rule", which describes that the sample size must be ten times the parameters, which has to be evaluated. This rule, though, only functions under certain circumstances (Hussain & Ahmed, 2020; Streukens & Leroi-Werelds, 2016). Power analysis techniques or simulation studies can be used to calculate the sample size required to attain a given power level, for instance, 80% or 90%, to establish the sample size that provides a high likelihood of detecting a particular effect. In general, SEM requires a sample size of 200 or more. However, this guideline might only apply to particular models; thus, employing more sophisticated sample size estimation techniques is always a good idea.

According to Kang (2021) and Hoenig and Heisey (2001), power analysis can decide the desired sample size to identify a particular effect size at a specific power level. Power analysis can consider the magnitude of measurement error, the complexity of the model, and the number of indicators. Simulators de Monte Carlo – this method simulates data and figures out the sample size necessary to accurately estimate model parameters (Hayes et al., 2017; Kroese et al., 2014). It can be accomplished by relating the Akaike information criterion (AIC) or the Bayesian information criterion (BIC) for various sample sizes. It is crucial to remember that sample size is only one consideration when evaluating the fit of a model. Several additional elements, for instance, the number of indicators, the considered model's complexity, the data distribution, and the estimation method, impact the model fit (Hoenig & Heisey, 2001).

Previous literature demonstrated that multicollinearity is a common problem in PLS-SEM and CB-SEM, which occurs when two or more predictor variables are closely associated (Grewal et al., 2004). It occurs when two or more independent variables exhibit strong correlations, and estimating models and explaining their results can be challenging (Wondola et al., 2020). For example, a correlation matrix can determine how every independent construct connects with others to find multicollinearity in PLS-SEM and CB-SEM. Multicollinearity may be present if there is a significant correlation between two or more independent constructs (Wondola et al., 2020). The degree of multicollinearity in a multiple regression model is measured by the variance inflation factor (VIF). The VIF of 1 shows the absence of multicollinearity, while a VIF bigger than 1 specifies the occurrence of multicollinearity. High multicollinearity is frequently indicated by a VIF more significant than five (Chan et al., 2022; Hussain & Ahmed, 2020). The variance amount in a predictor, which other predictors cannot describe, is represented by tolerance, which is the reciprocal of VIF. There is high multicollinearity when the tolerance value is below 0.2. The condition index gauges the level of multicollinearity in a multiple regression model. Multicollinearity is indicated by a number higher than 30 (Arminger & Schoenberg, 1989; Chan et al., 2022). The previous literature has discussed and identified several positive and negative aspects of PLS-SEM and CB-SEM techniques, however, numerous factors are still missing to establish the differentiation between both modeling techniques, thus the current study answers those questions.

2. Research methodology

2.1 Research design and estimation techniques

The undertaking is a comparative study, which has differentiated PLS-SEM and CB-SEM modeling; the study also considers the efficiencies and deficiencies of both models in the management sciences field. The comparative studies could be performed qualitatively or quantitatively. However, the research design of this study is qualitative, and researchers have stated the pros and cons of PLS-SEM and CB-SEM techniques; they also compare different parameters of both techniques. This study has used previous literature and thoroughly reviewed previous studies, books, and other relevant publications to analyze both models. This study also used graphical analysis to distinguish between PLS-SEM and CB-SEM modeling.

The study examined the criteria to validate measurement models, such as convergent and discriminant validities, using factor loading of items, Cronbach's alpha, composite reliability, and average variance extracted of constructs to validate the convergent validity and reliability in both PLS-SEM and CB-SEM techniques. Moreover, this study analyzed HTMT, Fornell-Larcker criterion, and cross-loading to validate discriminant validity for both SEM techniques. Similarly, this study also examined the parameters for validating a structural model for PLS-SEM modeling. For this purpose, the researchers used the coefficient of determination (R^2), effect size (f^2), path coefficient analysis (direct, indirect relationship of constructs), goodness of fit measures, and predictive relevance (Q^2).

This research used confirmatory factor analysis, structural equation modeling, path coefficient analysis (direct, indirect relationship of constructs), and goodness of fit measures to validate structural models in CB-SEM techniques. This study also used the graphical analysis to examine the observed, unobserved, convergent, and discriminant validity to endorse the measurement model for both PLS-SEM and CB-SEM techniques. The graphical analysis also defined the path coefficient relationship (direct and indirect relationship of constructs) to validate the structural model for both PLS-SEM and CB-SEM techniques.

2.2 Acronyms and full names

Tab. 1 exhibited the acronyms and full names of different abbreviations used in this paper.

Tab. 1: Acronyms and full names

Acronyms	Full names	Acronyms	Full names
PLS-SEM	Partial least square structural equation modeling	**PLS-CFA**	Partial least square confirmatory factor analysis
CB-SEM	Covariance-based structural equation modeling	**PLS-DA**	Partial least square discriminant analysis
SEM	Structural equation modeling	**LGCM**	Latent growth curve modeling
Smart-PLS	Smart partial least square software	**LCA**	Latent class analysis
Warp-PLS	Variance-based and factor-based structural equation modeling software	**SRMR**	Standardized root mean square residual
XLSTAT	Excel statistical software	**HTMT**	Heterotrait monotrait ratio of correlation
AMOS	Analysis of moment structures	**AVE**	Average variance extracted
LISREL	Linear structure relations	**D_ULS**	The squared euclidean distance
M-Plus	Microdia plus software	**AGFI**	Adjusted goodness of fit index
RMSEA	Root mean square error of approximation	**RNI**	Relative non-centrality index
CFI	Comparative fit index	**PCFI**	Parsimonious-adjusted fit index
GFI	The goodness of the fit index	**PNFI**	Parsimony-adjusted normed fit index
TLI	Tucker Lewis index	**G_D**	Geodesic distance
NFI	Normal fit index	**VIF**	Variance inflation factor

Source: own

3. Results and discussion

The results of this study demonstrated the parameters of the measurement and structural models for both PLS-SEM and CB-SEM techniques.

3.1 The measurement model in CB-SEM and PLS-SEM modeling

In PLS-SEM & CB-SEM modeling, validating the measurement model entails evaluating the fitness of the dataset and the reliability of indicators chosen to represent the latent variables (Hair et al., 2019). This procedure includes the following steps as the factor loadings indicate how intensely indicators and unobserved factors are linked. Significant factor loadings show that the indicators and latent variables are closely connected (Hair et al., 2014; Rigdon, 2016). Factor loadings have a conventional cut-off of 0.7, which can change depending on the research environment (Ringle et al., 2015). The measuring model must be validated by evaluating the indicators' reliability and validity. While validity narrates how well the indicators measure the latent variable, reliability refers to the indicators' consistency across time (Byrne, 2013; Ringle et al., 2015).

The model must offer a good match for the dataset; in PLS-SEM modeling, several fit indices, including R^2 and Q^2, can be applied to measure how well the model fixes the dataset. These indices show the percentage of the variance in outcome constructs the model justifications (Henseler et al., 2015; Parmar et al., 2022). Similarly, many fit indices, including the RMSEA, chi-square statistic, and comparative fit index (CFI), can be applied to measure the model's fitness in CB-SEM modeling (Hooper et al., 2008). The importance of path coefficients and the overall model should be tested by examining the structural model (Bentler & Bonett, 1980; Hair et al., 2022).

Suppose the factor loadings or the model do not match the data well. In that case, it may be essential to re-specify the model by modifying the path coefficients, adding or removing variables, or making other modifications (Sarstedt et al., 2022). It is essential to remember that measurement model validation is an iterative process, and the model should be refined and re-evaluated as needed until an acceptable level. It is crucial to remember that when working with CB-SEM, using multiple data sources, such as self-report surveys, behavioral observations, and physiological measures, can increase the rationality of the measurement model. Additionally, the validation process should be done with the sample used in the study and not just in the population in general (Hair et al., 2014). The annotated graphical form of the measurement model of PLS-SEM is provided in Fig. 1 (Ahmed et al., 2021). Fig. 1 demonstrated that the factor loadings of each item are higher than 0.70, and the average variance extracted is more significant than 0.50, which fulfilled the convergent validity requirement. Moreover, the path analysis between the construct validated the discriminant validity; thus, this endorsed the measurement model.

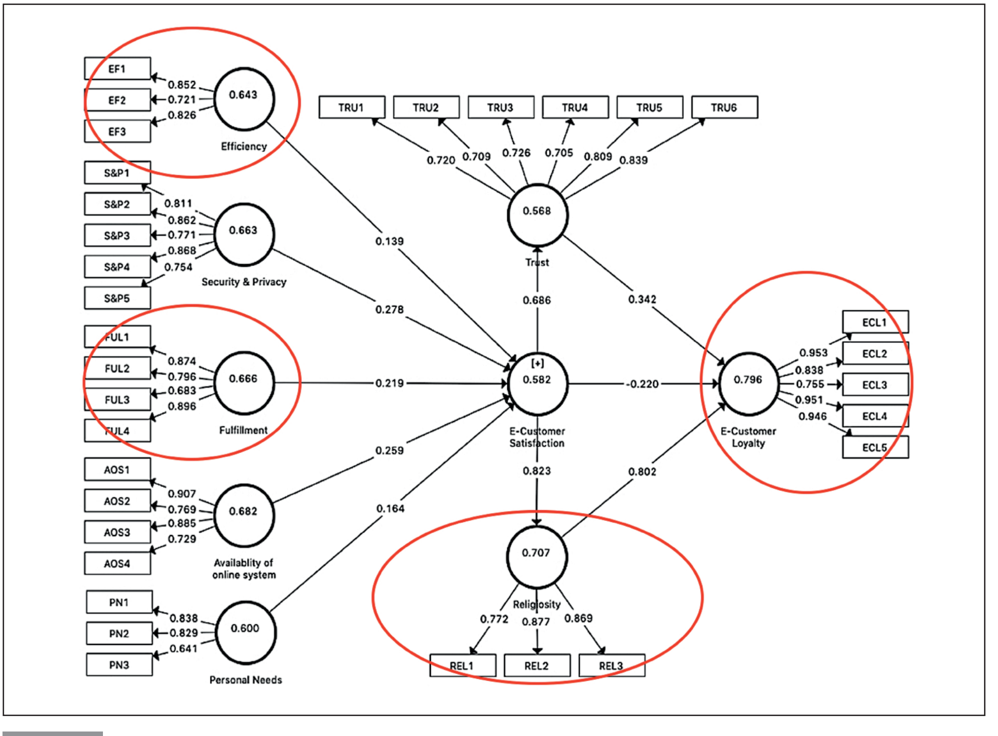

Fig. 1: **Measurement model in PLS-SEM modeling**

Source: Ahmed et al. (2021)

The annotated graphical form of the measurement model of CB-SEM is provided in Fig. 2 (Ashraf et al., 2018). Fig. 2 also demonstrated that each observed variable has a factor loading of more than 0.70, values of path coefficient between the unobserved variables, and values of goodness of fit measures have followed the cut-offs. Thus, Fig. 2 demonstrates that the measurement model is validated in CB-SEM modeling.

3.2 The structural model in CB-SEM and PLS-SEM modeling

In CB-SEM and PLS-SEM modeling, validating the structural model entails analyzing the model's fitness to the dataset, determining the importance of the path coefficient, and reviewing the overall model (Kline, 2015). This procedure includes several steps; for example, the path coefficients show how strong and in what direction the latent variables are related. High positive path coefficients indicate a strong positive relationship between the latent variables, while high negative path coefficients indicate a strong negative relationship (Hair et al., 2019; Raza et al., 2021). *T*-tests or bootstrapping techniques can be used to conclude the significance of the path coefficients. If the path coefficient is significant, the latent variables must be statistically related (Hair et al., 2014; Hayes et al., 2017; Henseler et al., 2015).

In PLS-SEM modeling, fit indices like R^2 and Q^2 could be applied to measure the overall fitness of the model. These indices indicate the variance proportion in dependent factors that the model explains (Bentler, 1990). The overall fitness of the CB-SEM model can be evaluated using fit indices such as the RMSEA, chi-square statistic, and comparative fit index (CFI; Hooper et al., 2008). Discriminant validity examines how little latent variables connect with measurements of unrelated constructs. It can

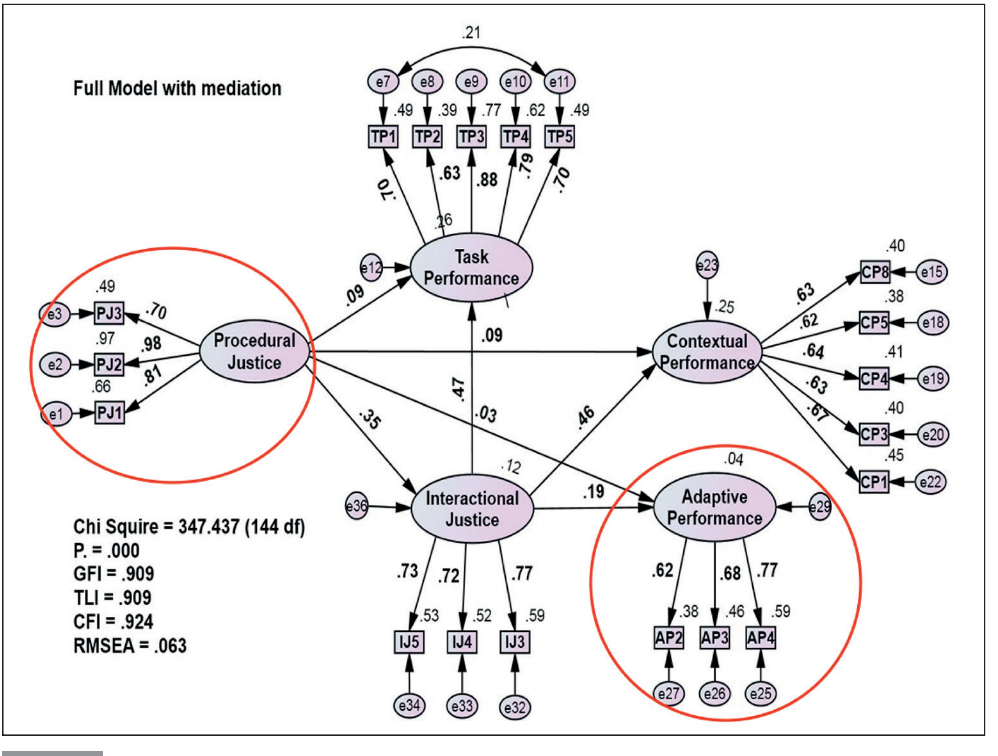

Fig. 2: **Measurement model in CB-SEM modeling**

Source: Ashraf et al. (2018)

be assessed by contrasting the latent variables' average variance extracted with their squared correlation to unrelated factors (Ahmed et al., 2021; Fornell & Larcker, 1981; Hair Jr. et al., 2017; Malhotra et al., 2006).

The model may need to be re-specified by adding or removing variables, changing the path coefficients, or modifying the model in other ways if it does not fit the data well or if the path coefficients are not significant (Kaufmann & Gaeckler, 2015; Sarstedt et al., 2022). It is crucial to remember that structural model validation is an iterative process. The model must be polished and reexamined until an acceptable fit level and significance are achieved (Sarstedt et al., 2019). It is essential to remember that when working with CB-SEM, using multiple data sources, such as self-report surveys, behavioral observations, and physiological measures, can increase the validity of the structural model. Additionally, the validation process should be done with the sample used in the study and not just in the population in general (Malhotra et al., 2006). The annotated graphical form depicted the structural model of PLS-SEM in Fig. 3 (Ahmed et al., 2021). Fig. 3 demonstrated the path coefficient between the constructs (direct and indirect relationship), which shows significant values; moreover, *R*-square values showed the impact of exogenous variables on endogenous variables. Thus, Fig. 3 validated the structural model in PLS-SEM modeling.

The annotated graphical shape of the structural model of CB-SEM is provided in Fig. 4 (Ashraf et al., 2018). Fig. 4 demonstrates the path coefficient between the constructs (direct and indirect relationship), which shows significant values. Moreover, fit indices values meet the required threshold. Thus, Fig. 4 validated the structural model for CB-SEM modeling.

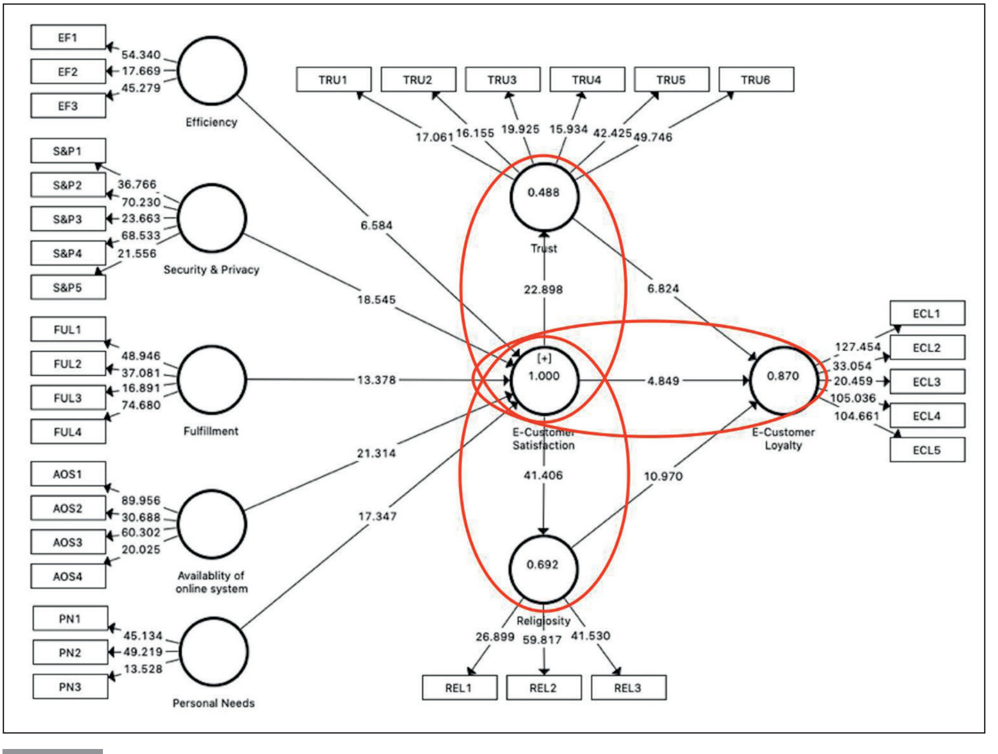

Fig. 3: **Structural model in PLS-SEM**

Source: Ahmed et al. (2021)

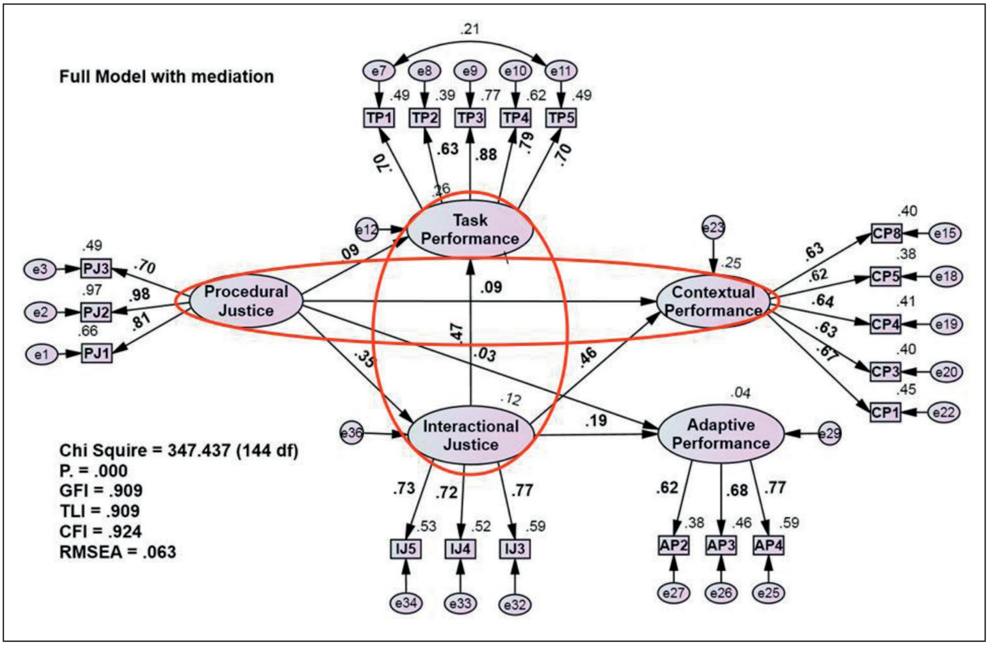

Fig. 4: **Structural model in CB-SEM**

Source: Ashraf et al. (2018)

3.3 Threshold values to validate the CB-SEM and PLS-SEM modeling

When validating a measurement or structural model in PLS-SEM or CB-SEM, several threshold values are commonly used to measure the accuracy, model, and reliability. Now, we have an overview of some of the most commonly used threshold values; for instance, a standard threshold for factor loadings is 0.70, but it can vary depending on the research context (Henseler et al., 2015; Kline, 2015). The typical Cronbach's alpha threshold is 0.70; however, it may change depending on the research situation (Hair et al., 2014; Miles & Shevlin, 2007).

Composite reliability depends on the research environment; the composite reliability criterion of 0.70 is typically adequate (Ringle et al., 2015). The AVE cut-off is often set at 0.50 but might change depending on the research environment. Good discriminant validity is often indicated by values higher than 0.50 (Fornell & Larcker, 1981; Hair et al., 2009).

Tab. 2: **Threshold values of reliability and validity**

Measures	Threshold values
Factor loading (FL)	Equal and higher 0.70
Cronbach's alpha (CA)	Equal and higher 0.70
Composite reliability (CR)	Equal and higher 0.70
Average variance extracted (AVE)	>0.50

Source: own

The typical correlation threshold is 0.70; however, it can change depending on the research circumstances. Correlations above 0.70 generally indicate a strong relationship between two variables (Hussain & Ahmed, 2020; Maydeu-Olivares et al., 2018). Tab. 2 exhibited the threshold values of factor loading, Cronbach's alpha, composite reliability, and average variance extracted.

3.4 The PLS-SEM modeling goodness of fit measures

In PLS-SEM, model fitness could be evaluated using a multiplicity of metrics, such as R^2, which gauges the proportion of the outcome construct's variance that could be accounted for by independent constructs (Hair et al., 2019). The variance amid the perceived projected covariance matrix is measured by the RMSEA, with readings nearer to 0 signifying a better fit (Hooper et al., 2008). The goodness-of-fit index (GFI) measures how considerably the variance in the observed variables can be accounted for by the model, with values nearer 1 suggesting a good fit (Hu & Bentler, 1999; Hair et al., 2019). The normal fit index (NFI), a variant of the GFI that accounts for the parameters in the considered model, has values closer to 1 than those that indicate a better fit (Ringle et al., 2022). The SRMR, a well-known measure fit of the overall model, is used in PLS-SEM. The SRMR measures the difference between observed and predicted covariance matrices. It varies from 0 to 1, where a value of 0 designates a complete fit, and a value of 1 specifies that the model cannot replicate the observed covariance matrices (Bollen & Davis, 2009). Less than 0.08 is the suggested cut-off value for the SRMR, which denotes an acceptable model fit to the dataset. However, the research field and sample size can affect the allowable value of SRMR (Ringle et al., 2015).

It is imperative to remember that SRMR is a sample-based measure calculated based on the sample, not the population. Moreover, it takes into account both structural and measurement models. It is not sensitive to the sample size; thus, it is a more robust gauge for model fit than other fit statistics such as RMSEA or CFI (Henseler et al., 2015; Kline, 2015). The CFI should be 1 for saturated models, and the RMSEA should be close to 0. It means that the model accurately describes all variations in the observed variables and is a perfect fit for the dataset (Hair et al., 2019; Mouri, 2005). RMSEA < 0.08 and CFI > 0.95 are the suggested cut-off values for estimated models. These results demonstrate that the model demonstrates the relationship among variables in the data and fits the data very well. These cut-off numbers, however, may change based on the research area and circumstance (Memon et al., 2019; Raza et al., 2021). CFI (comparative fit index) is comparable to NFI but also justifies the complexity of the model compared to a null model, with values closer to 1 suggesting a better match (Bentler, 1990; Bollen & Davis, 2009). It is worth noting that no one metric is a silver bullet, and it is consistently substantial to evaluate different metrics for different purposes (Hair et al., 2018; McDonald & Ho, 2002).

3.5 Discriminant validity in PLS-SEM

Discriminant validity in PLS-SEM refers to a construct's or latent variable's capacity to stand out from other constructs or unobserved constructs' in the considered model. It ensures that the factor measures what it intends to measure and not some other construct (Cheah et al., 2019; Raza et al., 2021). There are various techniques to evaluate the discriminant validity of PLS-SEM; for instance, the correlation ratio relates the connection between two factors to the square root of the AVE of one component. The ratio must be more significant than one to prove discriminant validity (Chin, 2010; Fornell & Larcker, 1981).

The Fornell-Larcker criterion equates the squared correlation between an indicator and the unobserved construct to the product of the unobserved construct's AVE, the indicator's squared loading on the latent variable (Cohen, 1994; Fornell & Larcker, 1981). D_ULS (discriminant validity – uniqueness) and D_G (discriminant validity – Fornell-Larcker criterion) are measures of the degree to which a factor's variance is unique, meaning other factors do not explain it in the model. A high D_ULS or D_G value indicates a construct's uniqueness, which is desirable for good discriminant validity (Franke & Sarstedt, 2019; Henseler et al., 2015).

The suggested cut-off value for D_ULS and D_G is typically more than 0.5. However, the acceptable value of D_ULS and D_G may change based on the investigation area, the size of the sample, and the research circumstances (Ringle et al., 2022). It is significant to remember that D_G and D_ULS are not the only processes for discriminant validity. Other measures can be used, such as cross-loadings, AVE (average variance extracted), or the Fornell-Larcker criterion (Fornell & Larcker, 1981; Henseler, 2021). While these techniques can aid in establishing discriminant validity, it is essential to keep in mind that they should be used in conjunction with other approaches, for instance, Factor loading evaluation, cross-loading, correlation matrix evaluation, and model-specific theoretical construct and relationship analysis (Ahmed et al., 2020; Hult et al., 2018).

3.6 F-square values in PLS-SEM

F-square values are frequently used in PLS-SEM to measure the relative significance of predictors. The F-square value gauges how much of a dependent variable's variance each predictor contributes to (Henseler et al., 2015; Hwang et al., 2020). Each predictor in the model has an F-square value ranging from 0 to 1, with 1 denoting that the predictor fully explicates the variance in an outcome construct (Ringle et al., 2015). F-square values can be used to compare the relative weights of several model predictors. For example, a predictor with an F-square value of 0.8 would be considered more critical than one with an F-square value of 0.2 (Sarstedt et al., 2022). It is critical to remember that F-square values are relative measurements determined by the proportion of variance explicated through the model's predictors, not by the total amount of variance explicated (Ahmed et al., 2019). Moreover, PLS-regression (PLS-R) is the only version that supports it; PLS-path modeling (PLS-PM) does not (Henseler et al., 2015).

3.7 Predictive relevance (Q2) in PLS-SEM

Predictive relevance, sometimes referred to as Q^2, is used in PLS-SEM to assess the model's capacity for prediction. It is a measurement of the percentage of an outcome construct's variation that the latent constructs in the model can accurately predict (Henseler et al., 2015; Liengaard et al., 2021). The PLS-SEM model's foreseen values for an outcome variable are compared to the actual values for the dependent variable to determine Q^2. The relevant research subject and environment will determine the appropriate value of Q^2 (Hair et al., 2017; Ringle et al., 2015; Shmueli et al., 2019). It is crucial to remember that Q^2 is a relative measure, meaning that the proportion of deviation determines it explained through the model rather than the total variance (Henseler, 2021; Shi & Maydeu-Olivares, 2020). Tab. 3 indicates the interpretations of predictive relevance (Q^2) values.

Tab. 3: Predictive relevance (Q^2)

Predictive relevance (Q^2) values	Interpretations
$Q^2 = 0$	A Q^2 value of 0 means the model cannot forecast any deviation in an outcome construct
$Q^2 \geq 0.5$	Q^2 values of 0.5 or above have good predictive power in real-world applications
$Q^2 = 1$	A Q^2 value of 1 means the model can perfectly forecast all deviations in an outcome construct

Source: own

3.8 Confirmatory factor analysis (CFA) in CB-SEM modeling

A statistical technique called CFA is employed in (CB-SEM) to examine a measurement model structure. A latent variable estimate based on several indications is possible using CB-SEM. The factor structure of the indicators and the connection between the unobserved variables and the indicators are tested using CFA (Zhang et al., 2020). By contrasting the manifest covariance matrix with the projected covariance matrix based on loadings and error variances of indicators, CFA is modified to assess the measurement structure of the model in CB-SEM. If the observed and projected covariance matrices match, the model is deemed a well-fit (Raza et al., 2021).

CB-SEM also uses CFA to examine a measurement model invariance through clusters or time. It denotes the predicted consistency of the element configuration and the link between the unobserved variables and the indicators across groups or time (Ahmed et al., 2022; Bollen & Davis, 2009). It is vital to remember that CFA is a confirmatory technique that examines a particular theory regarding the factor structure and the relationship between the unobserved variables and indicators. Also, it is crucial to note that CFA is a typical and crucial stage in CB-SEM modeling, earlier touching on the structural model component (Hair et al., 2019).

3.9 Structural equation modeling in CB-SEM modeling

CB-SEM uses structural equation modeling, a statistical approach to examine the structural links between latent and observable variables. Complex models with numerous unobserved constructs and indicators for every construct can be estimated using SEM (Ahmed et al., 2019; Hair et al., 2022). CB-SEM uses SEM to measure the structural links between the latent and observable variables by estimating the path coefficients and error variances of unobserved constructs and indicators. If the observed and projected covariance matrices match, the considered model fits well.

A range of hypotheses can be tested using CB-SEM, including those involving direct and indirect effects, mediation and moderation effects, and latent interactions. CB-SEM can also be attuned to test for measurement invariance across groups or time (Hair et al., 2019; Raza et al., 2021; Zhang et al., 2020). In order to test a specific hypothesis about the structural associations among the unobserved and observable constructs, SEM is a confirmatory method, which is essential to note. Moreover, after establishing the measurement framework and associations among the unobserved constructs, SEM is a typical and crucial stage in CB-SEM modeling (Kline, 2015).

3.10 The CB-SEM modeling goodness of fit measures

The goodness-of-fit of the measurement and structural models is measured through fit indices in CB-SEM. They indicate how well the model captures the data and can be used to pinpoint areas where the model requires improvement (Byrne, 2013; Hooper et al., 2008). Several fit indices in CB-SEM, such as χ^2/df and probability, are known as the absolute fit indices in CB-SEM modeling (Bentler & Bonett, 1980; Bollen, 1989; Lu et al., 2020). The goodness-of-fit index (GFI) indicator evaluates an association between the model's justified covariance and the data's total covariance (Byrne, 2013; Hu & Bentler, 1999). The adjusted goodness-of-fit

Tab. 4: Fit indices and threshold values

Fit-indices	Threshold values
χ^2/df and probability	χ^2/df > 5.0 and $p < 0.05$
GFI	Range of 0 to 1, with values around 1 (>0.95) a solid fit
AGFI	AGFI varies from 0 to 1, with a reading close to 1 (>0.95) satisfactory fit
RMSEA	<0.05 good fit, between 0.05 and 0.10 acceptable, and >0.10 poor fit
SRMR	A good fit is indicated by values less than 0.08, a good fit is shown by readings ranges 0.08–0.10, and a poor fit is indicated by readings higher than 0.10
RNI	The RNI index is 0 to 1, with values nearer 1 (>0.95), indicating a better model-to-data fit
CFI	>0.90 acceptable and >0.95 good fit
NFI	The NFI index is 0 to 1, with values nearer 1 (>0.95), indicating a better model-to-data fit
PCFI	0.75 or higher
PNFI	0.75 or higher

Source: own

index (AGFI), an amended form of the GFI, takes into account the model's independent variable count, the absolute fit indices, also known as the GFI and AGFI (Barbić et al., 2019; Bentler, 1990). The RMSEA measures the inconsistency amid the manifest and anticipated covariance matrix (Tanaka, 1993). The standard root mean square residual (SRMR) metric contrasts the model's residuals with the variances of the observed variables (Hooper et al., 2008; Ringle et al., 2015). The RNI (relative non-centrality index) fit index is a statistical metric to assess how sound a model fits a specific dataset collection. Considering the variance of the observed values, it calculates the variance amid the actual values and values forecasted through the model (Ahmed et al., 2021; Oliver, 2014). Other frequently used fit indices in CB-SEM are the comparative fit index (CFI), Trucker-Lewis index (TLI), and normal fit index (NFI). These are comparable to traditional SEM's goodness-of-fit index (GFI) and adjusted goodness-of-fit index (AGFI) (Hair et al., 2019; Raza et al., 2021; Tucker & Lewis, 1973).

To calculate PCFI (parsimonious-adjusted fit index), subtract the model's CFI from the CFI of a null model, then divide the outcome by the change in degrees of freedom between the two models (Barbić et al., 2019; Bentler, 1990; Blackwell et al., 2001; Byrne, 2013). The difference between the model's normalized fit index and the normalized fit index of a null model is used to produce the PNFI (parsimony-adjusted normed fit index), which is then divided by the variance in degrees of freedom between the two models (Hu & Bentler, 1999). It is critical to understand that many fit indices must be calibrated to estimate the model and that no single fit index is considered the best. The context of the research topic and the study's objectives must be justified while assessing the fit indices (Astrachan et al., 2014; Hair et al., 2019; Tucker & Lewis, 1973). Threshold values of fit indices are exhibited in Tab. 4.

Conclusions

The CB-SEM is a powerful technique for analyzing complex relationships among multiple variables. Both methods have advantages and disadvantages, and the approach relies on the study issue, the availability of resources, and the time available. PLS-SEM is a robust technique that can handle high levels of measurement error and can be applied to small and unbalanced datasets. It helps look at correlations between unobserved factors that are one, which could not be observed directly. When conventional SEM is not practical, PLS-SEM is especially helpful. On the other hand, CB-SEM is a powerful technique that can handle numerous groups and various signs. It helps examine connections between several manifest factors, or those that can be directly observed, and numerous latent variables (Henseler et al., 2015; Kline, 2015). CB-SEM is especially helpful when the objective is to generalize findings to specific demographic subgroups. PLS-SEM and CB-SEM are valuable tools for examining structural equation models. The study question and the characteristics of the population being investigated influence the technique selection. When selecting the best technique for their research, researchers must consider both approaches' drawbacks and underlying assumptions. The research issue and the features of the population being examined determine the theoretical implications of the comparison between CB-SEM and PLS-SEM (Ahmed et al., 2021). PLS-SEM is a data-driven approach that does not rely on a priori postulations regarding the structure of the associations among factors. Researchers can use PLS-SEM to uncover latent relationships among variables that may not be immediately apparent from the data. It can benefit researchers interested in exploring new or complex relationships among variables (Hair et al., 2022). Contrarily, CB-SEM is more theory-driven and is based on presumptions about the structure of the correlations among factors. To test particular propositions regarding the relationships between factors, researchers can employ CB-SEM. Researchers interested in putting tested theories or hypotheses to the test may find it helpful. PLS-SEM offers greater flexibility and exploration of the data, whereas CB-SEM offers greater rigor and testing of particular hypotheses. Both methods have advantages and limitations, and the choice of which technique to use depends on the characteristics of the population research question being studied (Hair et al., 2019; Zhang et al., 2020).

Additionally, PLS-SEM is more robust to multicollinearity and measurement error, which can be an issue in CB-SEM, where the assumptions of independence among the predictors and measurement invariance across groups should be met. PLS-SEM is viewed as a more recent and less well-established technique than CB-SEM; despite this, PLS-SEM is becoming more and more well-liked and common in use, particularly in industries like marketing, psychology, and management (Ahmed et al., 2022; Hair et al., 2022). The study issue and the characteristics of the population will determine the managerial implications of the comparison between CB-SEM and PLS-SEM. PLS-SEM is a dominant procedure that can handle high measurement error levels, small and unbalanced datasets, and latent variables. PLS-SEM could be used in conditions where traditional SEM would be infeasible. Even when the sample size is unbalanced or small, and the measurement error is significant, PLS-SEM can be particularly valuable for managers and practitioners interested in understanding the underlying relationships among factors (Wondola et al., 2020). On the contrary, CB-SEM is a powerful technique that can handle numerous groups and various signs. CB-SEM can be applied when the goal is to generalize results to specific population subgroups. CB-SEM can be particularly useful for managers and practitioners interested in understanding associations between multiple unobserved and manifest factors and generalizing results to specific population subgroups. PLS-SEM offers greater flexibility and data exploration, whereas CB-SEM allows for more incredible rigors and testing of particular hypotheses, which has managerial consequences. The decision of which methodology to employ relies on the research issue and the characteristics of the population being examined. Both methods offer benefits and drawbacks (Kline, 2015). Additionally, PLS-SEM is more robust to multicollinearity and measurement error, which can be an issue in CB-SEM, where the assumptions of independence among the predictors and measurement invariance across groups should be met. It is also significant to note that PLS-SEM can be helpful in practice, particularly in industries like marketing, psychology, and management, where practitioners and researchers must deal with complicated and unbalanced datasets and where an exploratory approach is required (Henseler, 2021; Shi & Maydeu-Olivares, 2020).

Limitations and future research orientations

PLS-SEM and CB-SEM are powerful techniques for analyzing complex relationships among multiple variables; however, they also have some limitations. Some of the limitations of PLS-SEM include the following: PLS-SEM is less established and less well-known than traditional SEM, which may be less familiar to some researchers (Wondola et al., 2020). PLS-SEM does not rely on a priori suppositions regarding the structure of the relationships among the factors, making interpreting the results challenging (Hair et al., 2022). Thus, it is recommended that future researchers study this limitation. PLS-SEM is sensitive to outliers and extreme observations, which can affect the analysis results. PLS-SEM does not offer a test for overall model fit. The following are some CB-SEM drawbacks: when a priori postulations vis-à-vis the nature of interactions between the factors are not achieved, CB-SEM is used, making it challenging to interpret the results. Thus, it is recommended that future researchers carry out their studies on this topic. Another critical limitation of PLS-SEM & CB-SEM modeling is not to provide a cause-effect between the constructs (Ahmed et al., 2022). Therefore, it is recommended that the researchers establish cause and effect between the variables; they must use some additional models, including Toda and Yamamoto (1995).

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