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CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting

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ABSTRACT

This study compares the two widely used methods of Structural Equation Modeling (SEM): Covariance based Structural Equation Modeling (CB-SEM) and Partial Least Squares based Structural Equation Modeling (PLS-SEM). The first approach is based on covariance, and the second one is based on variance (partial least squares). It further assesses the difference between PLS and Consistent PLS algorithms. To assess the same, empirical data is used. Four hundred sixty-six respondents from India, Saudi Arabia, South Africa, the USA, and few other countries are considered. The structural model is tested with the help of both approaches. Findings indicate that the item loadings are usually higher in PLS-SEM than CB-SEM. The structural relationship is closer to CB-SEM if a consistent PLS algorithm is undertaken in PLS-SEM. It is also found that average variance extracted (AVE) and composite reliability (CR) values are higher in the PLS-SEM method, indicating better construct reliability and validity. CB-SEM is better in providing model fit indices, whereas PLS-SEM fit indices are still evolving. CB-SEM models are better for factor-based models like ours, whereas composite-based models provide excellent outcomes in PLS-SEM. This study contributes to the existing literature significantly by providing an empirical comparison of all the three methods for predictive research domains. The multi-national context makes the study relevant and replicable universally. We call for researchers to revisit the widely used SEM approaches, especially using appropriate SEM methods for factor-based and composite-based models.

1. Introduction

SEM (Structural Equation Modeling) is usually used to explain multiple statistical relationships simultaneously through visualization and model validation. Complex models can be discussed simply through this technique. It is an extension of traditional linear modeling techniques, e.g., multiple regression analysis and Analysis of Variance (ANOVA), prerequisites for learning SEM. Briefly, it can be defined as a combination of factor analyses and multiple regression analyses simultaneously (Sarstedt et al., 2017; Hair Jr et al., 2017a; Haenlein and Kaplan, 2004). SEM aims to understand the relationship between latent constructs (factors) that are generally indicated by various measures. It is also known as latent variable analysis as well as covariance structure analysis. It adopts a confirmatory approach rather than an exploratory one. Some of the unique features of SEM can be summarized as follows: Latent factors are explained through dependence relationships and are typically called constructs (Hooper et al., 2008); It provides a single complex model that includes various dependence and interdependence relationships among the constructs; The covariance between the observed variables is explained by this method with detailed analysis of various covariance statistics, e.g., mean, standard deviation, etc.; Recently, the PLS approach has become quite popular among researchers due to its variance based relationship rather than covariance (AlNuaimi et al., 2021; Mueller & Hancock, 2018; Hair Jr et al., 2017b; Hayes et al., 2017); It is different from the traditional multivariate techniques that address only individual objectives; It also verifies alternate models to find the most appropriate relationship among the latent variables. It usually deals with a large sample (Mueller & Hancock, 2018; Hair Jr et al., 2017b; Hayes et al., 2017; Ullman & Bentler, 2003).

The purpose of this paper is to compare both approaches based on various parameters and to provide a possible solution to the dilemma. The rest of the paper is structured as follows. Section 2 discusses the scope of the paper, which explains the need for this study, the objectives,

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and the research questions. It also includes the contributions of the study. Section 3 highlights the various characteristics of SEM, especially the statistics and fit indices involved. Section 4 details the process of SEM in a stepwise manner. Section 5 compares the three types we have undertaken. First, CB-SEM is compared with PLS-SEM. Then, PLS and PLSc are compared. Next, a piece of empirical evidence is provided in section 6. In this section, all the empirical results from all three methods are discussed and compared. Sections 7 and 8 provide a general discussion, future directions, and limitations. Finally, section 9 concludes this study.

2. The scope of the paper

In the last decade, there has been controversy regarding specific methods of Structural Equation Modelling. One school of thought completely disregarded PLS (Rönkkö et al., 2016), whereas the other researchers countered with evidence and tried to dispel the misconception about the same (Sarstedt et al., 2016; Rigdon, 2016). There has been little attempt to try both CB-SEM and PLS-SEM approaches in consumer behavior and predictive research to compare the results. The objective of this study is to find out the better one under different circumstances. In a nutshell, the authors tried to answer two primary questions: RQ1: which one is the better approach: CB-based model or a PLS-based model? For the same data (sample group), which one is better to be adopted (a piece of empirical evidence is provided)? RQ2: How do PLS and PLSc (consistent) differ, and which one is the actual counterpart of CB-SEM?

This study contributes to the existing literature significantly by providing an empirical comparison of all the three methods for consumer behavior and predictive research domain. The multi-national context makes the study relevant and replicable universally. Researchers have vast implications to revisit the widely used SEM approaches, especially using appropriate SEM methods for factor-based and composite-based models. Although these are the primary objectives of this study, we seek to provide a comprehensive picture of various aspects of SEM, e.g., statistics and fit indices used in both the approaches; the sequential process of SEM; reporting of the results; future directions, and limitations in research studies.

3. SEM characteristics

3.1. SEM measurement model and path analysis

SEM is used as a universal tool to study experimental and non-experimental data. Similarly, it can be used for both types of cross-sectional and longitudinal data. Because of its flexibility and generality, this method has become hugely popular across numerous disciplines (Mueller & Hancock, 2018; Ullman & Bentler, 2003). The complex theoretical model developed using this method is typically linked with the data collected to validate it. This linkage is called model-data fit. Any theoretical model can be evaluated for this kind of fitness with available empirical data. SEM is considered a large sample method that usually demands a minimum sample size of 200. Three factors typically decide the sample size: type of distribution (observed variables), model complexity as well as the kind of method used for estimation (Hayes et al., 2017; Kiem, 2000). SEM evaluates two models: path analysis and measurement model. Some advanced models are also considered by it, such as multilevel models and growth models. However, in this study, we confine ourselves to i) measurement model and ii) path analysis. These two models were discussed first before going further.

3.1.1. Measurement model

Before discussing the path analysis among the latent variables (factors/ constructs), measurement of these unobserved variables was discussed first. These cannot be measured directly; hence numerous observed variables are calculated first, and latent variables or constructs are derived from these indicators. Each latent variable is measured by observed variables that are tested for reliability and validity. SEM uses Confirmatory Factor Analysis (CFA) to assess the measurement model (Hair Jr et al., 2020 Hayes et al., 2017). It is different from Exploratory Factor Analysis (EFA) as it verifies the already available factor specification with empirical data. Model fit is evaluated for CFA to validate the measurement. Once the model fit is done, the path models among the latent variables are assessed.

3.1.2. Path analysis

Path model is a case of multiple regression models estimated simultaneously. It can be mediation, moderation as well as interaction relationship among variables. The structural relationship among the latent variables is established vs. the observed indicators (observed variables). The path can be causal or covariance-based once the measurement models of the latent constructs are validated through CFA. It can test the unidimensionality, validity, and reliability of an unobserved latent construct (factor) (Mueller & Hancock, 2018; Hair Jr et al., 2017b; Malhotra et al., 2006). Hence, CFA should be conducted first for all the factors before establishing the relationships among them.

3.2. Statistics and fit indices in SEM

Though numerous measures are used to test SEM models, we will focus on the most important ones to understand them in detail. Before moving to the next section, the various fit indices and their threshold levels were summarized (Hooper et al., 2008). Absolute Fit Indices: these are derived from the fit of the obtained, imply covariance matrices, and do not use an alternative model as a base for comparison. Absolute fit indices demonstrate which proposed model best fits all available models and determine the match between sample data and a priori model (McDonald and Ho, 2002). Incremental Fit Indices: Compared to a null model, these measures evaluate the incremental, comparative, or relative fitness of the model (Miles and Shevlin, 2007; McDonald and Ho, 2002). Because of these natures, this is known as comparative. Parsimonious Fit Indices: these are relative fit indices derived from the above two categories. It penalizes complex models and incentivizes simpler models (Hooper et al., 2008; Mulaik et al., 1989). It is usually used to compare models.

3.2.1. Fit indices

3.2.1.1. Chi-square. Overall model fit is assessed by chi-square value. It tests the discrepancy between the sample and the matrices of covariance fitted in the model. It is usually considered as the badness of fit measure. It would show a not-so-significant value at 0.05 level (Kline, 2015; Hooper et al., 2008). The main problem with it is that it goes up with the sample size and number of indicators. Hence, other fit indices must be considered to take a decision (Shi & Maydeu-Olivares, 2020; Mueller & Hancock, 2018). Chi-square upon the degree of freedom gives a clear picture. CMIN/df value of 3 (in some cases, even up to 5) or less is considered a good model fit measure.

3.2.1.2. Goodness-of-fit statistic (GFI). (Jöreskog and Sörbom, 1993) provided an alternative to the chi-square test. It estimates the proportion of the variance provided by the projected covariance of the population. It ranges from 0 to 1. Usually, the widely recommended threshold is 0.90, but for small samples and lower factor loadings, it should be more than 0.95 (Hair Jr et al., 2017a; Miles and Shevlin, 2007)

3.2.1.3. Adjusted goodness-of-fit statistic (AGFI). It is derived from GFI. It tries to adjust the GFI with degrees of freedom. For example, mean squares are used instead of the sum of squares (used in GFI). It also ranges from 0 to 1. Usually, the widely recommended threshold is 0.90. (Shi & Maydeu-Olivares, 2020; (Jöreskog and Sörbom, 1993))

3.2.1.4. Root mean square error of approximation (RMSEA). (Steiger and Lind, 1980)developed the model that advocates parsimony. It is considered the best informative fit index. It goes for an optimal number of parameters (lesser) to fit the final population covariance matrix. Thus, a good model fit should have an RMSEA value of 0.07 or less. (Shi & Maydeu-Olivares, 2020; Browne and Cudeck, 1993)

3.2.1.5. Root mean square residuals (RMSR). It is obtained by taking the square root of the mean of the residuals of the sample covariance matrix and the proposed covariance model. Fitted residuals should be measured by comparing the hypothesized covariance matrix and the sample covariance matrix (Kline, 2005). It should be closer to 0 for a better model fit. It is closely linked to the number of levels in the items of a questionnaire (Shi & Maydeu-Olivares, 2020; Maydeu-Olivares et al., 2018). If the numbers vary, e.g., one item with five levels and another with seven levels, it becomes difficult to calculate.

3.2.1.6. Standardized RMSR (SRMR). It solves the problem faced by RMSR and can be interpreted easily. The range lies between 0 to 1. It is calculated by dividing the fitted residuals by the standard error of the residual. The lower the value is, the better the model fit. A threshold value of 0.05 or less is accepted widely (Shi & Maydeu-Olivares, 2020; Maydeu-Olivares et al., 2018). A value of up to 0.08 is also considered acceptable (Hu and Bentler, 1999).

3.2.1.7. Normed fit index (NFI). This index evaluated the model by comparing the chi-square value of the model and the same null model or independence model (Bentler and Bonett, 1980). The null model means that all the measured variables/ indicators are uncorrelated, usually the worst possible scenario. Hence, the improvement can be assessed by considering NFI. A threshold value of 0.90 and above suggests a good model fit. Some studies recommended > 0.95 (Hu and Bentler, 1999). However, it is again highly affected by sample size; hence it cannot be considered alone.

3.2.1.8. Non-normed fit index (NNFI). It solves the problem posed by NFI. It is also called (Tucker and Lewis, 1973) Index. It promotes simpler models and discourages complex models. It is not affected by the low sample size. A threshold value of 0.90 and above suggests a good model fit. TLI typically produces values less than GFI. (Hair Jr et al., 2020; Bentler, 1990). The major limitation with this index is that it can go beyond one and might be complicated from an interpretation perspective (Hooper et al., 2008).

3.2.1.9. Comparative fit index (CFI). Bentler (1990) provided a renovated NFI to take care of a small sample size. It also compares the model fit with a null or independent model. The significant difference is that it talks about the latent factors rather than indicators. A threshold value of 0.90 (>0.95 in small samples) and above suggests a good model fit (exact as NFI) ((Hair Jr et al., 2020); Maydeu-Olivares et al., 2018). It is one of the most popular indices used in SEM.

3.2.1.10. Relative fit index (RFI). Though the normal range is between 0 and 1, it goes beyond the range too. Usually, a value closer to 1 indicates a better model fit (Hu & Bentler, 1999; Tanaka, 1993).

3.2.1.11. Parsimonious fit measures. The Parsimonious Goodness-of-Fit Index (PGFI) and the Parsimonious Normed Fit Index (PNFI) were introduced to penalize the complexity of the model (Mulaik et al., 1989). PGFI is derived from GFI, and PNFI is derived from NFI. In addition, the Parsimonious Comparative Fit Index (PCFI) was included as an extra measure. These measures should be used in sync with absolute and relative fit measures. Although no specific cut-off values are suggested, 0.5 is usually considered to be good enough (Hooper et al., 2008).

All the fitness indices with cutoff marks are provided in Table-1.

Table. 1
Three Types of Models Fit and Level of Acceptance.

Type	Index	Ideal Threshold value
Absolute Fit Measures	Chi-square of the estimated model	p-value>0.05
	CMIN/df	<3 (even <5)
	Goodness-of-fit Index (GFI)	>0.95 (0.90 too)
	Adjusted goodness-of-fit Index (AGFI)	>0.90
	Standardized Root mean square residual (SRMSR)	<0.05
	Root mean square error of approximation (RMSEA)	<0.08
Incremental Fit Measures	Tucker-Lewis Index (TLI)	>0.90
	Normed Fit Index (NFI)	>0.90
	Comparative Fit Index (CFI)	>0.95
Parsimonious Fit Measures	Parsimonious Goodness of Fit Index (PGFI)	>0.50
	Parsimonious Normed Fit Index (PNFI)	>0.50
	Parsimonious Comparative Fit Index (PCFI)	>0.50

4. The process of SEM

All the relationships among the latent variables and the observed variables are represented in an integrated model through SEM. The process of SEM involves various steps that are discussed in detail.

Steps Involved in the Process of SEM

Step 1: Individual Constructs

Individual Constructs must be adequately defined. All the latent variables (constructs) must be shown in a hypothesized model. These constructs must be based on two types of theories: structural and measurement. Hence, theories must be the primary base to define the individual constructs. (Hair Jr et al., 2020; Maydeu-Olivares et al., 2018; Bentler, 1990)

Step 2: Preparing for CFA

Once the constructs are defined, the measurement model must be specified. All the variables (indicators) should be drawn against the factors/ constructs, and the path diagram should be developed. Loadings of the indicators should be shown too. To complete the model, error terms must be added wherever applicable. (Dash et al, 2021; Dash & Chakraborty, 2021; Shi & Maydeu-Olivares, 2020)

Step 3: Running CFA

Before moving further, the specified measurement model must be assessed for Reliability as well as Validity. Then, the model's reliability can be evaluated, and the composite reliability (aggregation of the indicators under a latent variable). Again, it should be more than 0.6. Another tool to assess reliability is Average Variance Extracted (AVE). Again, it should be more than 0.5 for each construct.

Further, both convergent and discriminant validity are evaluated to ascertain the measurement models' nature. All the indicators under a latent variable must have high loadings of more than 0.6, providing good convergent validity (Shi & Maydeu-Olivares, 2020; Hair et al., 2017a; Malhotra et al., 2006). On the other hand, one indicator must load highly only on one latent construct. Cross loading must be avoided. Each construct must be distinct from others to provide a case of discriminant validity. Another essential requirement is Unidimensionality. It is achieved when all indicators under a latent construct have an acceptable factor loading of 0.6 and above (Hair et al., 2010; Malhotra et al., 2006). To check the normality of the data, skewness and kurtosis are assessed. The ideal range for these two measures lies between -2 to +2 (Hu & Bentler, 1999). Once reliability and validity are assessed, the model is evaluated for model fit. It includes all three categories of model fit indices: absolute, incremental, and parsimonious. After considering the model fit, modification can be undertaken if required. This is done by taking care of high covariance among measurable indicators (Dash et al., 2021; (Hair Jr et al., 2020)).

Step 4: Structural Modeling

Now the focus moves to the relationship among constructs. First,

structural linkage based on the available theories is established between the latent variables. Then, the hypothesized model is assessed for validity and model fit (all three types). Next, all the structural relationships are tested (hypothesis testing) with the help of relevant statistical tools, especially regression/ path coefficients (Mueller & Hancock, 2018; Hair Jr et al., 2017b; Hayes et al., 2017; Ullman & Bentler, 2003). It can be compared with similar models too. Finally, empirical data is fed into the model to test the validity of the underlying theories.

Step 5: Findings

Finally, based on the findings out of the model, various conclusions as per objectives can be drawn. Similarly, suitable recommendations and suggestions can be offered based on the statistical results (Dash et al., 2021; (Hair et al., 2010)).

5. SEM: different types

5.1. CB-SEM versus PLS-SEM

Though numerous statistical packages are available to study the concept of SEM, we will limit ourselves to two of these packages. IBM SPSS Amos (Analysis of Moment Structures) (IBM Corp, 2016) and Smart PLS (Partial Least Squares) (Ringle et al., 2015) are discussed in this paper. After evaluating all the packages, these two are selected because of their user-friendliness and global reach. Both the software have their pros and cons. Amos is a tool based on covariance, whereas Smart PLS is based on partial least squares (variance/ regression) (Sarstedt et al., 2017; Hair Jr et al., 2017a; Haenlein and Kaplan, 2004).

"IBM® SPSS® Amos is a powerful structural equation modeling software that enables you to support your research and theories by extending standard multivariate analysis methods, including regression, factor analysis, correlation, and analysis of variance. With SPSS Amos, one can build attitudinal and behavioral models that reflect complex relationships more accurately than with standard multivariate statistics techniques using either an intuitive graphical or programmatic user interface." (IBM, 2017).

"The philosophical distinction between CB-SEM and PLS-SEM is straightforward. If the research objective is theory testing and confirmation, then the appropriate method is CB-SEM. In contrast, if the research objective is prediction and theory development, then the appropriate method is PLS-SEM. Conceptually and practically, PLS-SEM is similar to using multiple regression analysis. The primary objective is to maximize explained variance in the dependent constructs but additionally to evaluate the data quality based on measurement model characteristics." (Hair Jr et al., 2017a). Amos is more stringent compared to Smart PLS (SPLS). If formal theory and the appropriate sample size are not available, SPLS can work, but Amos does not give a proper model fit. In the words of Hair (2017a), "both the methods are complementary, not competitive." Choice of the method originates from the goal of the research. If the existing theory needs to be tested and confirmed, CB-SEM is the chosen one. Nevertheless, for theory development as well as prediction purposes, PLS-SEM is better.

5.2. PLS-SEM and PLSc-SEM

PLS-SEM is divided into two aspects. One deals with prediction-based studies (PLS-SEM), whereas the other deals with testing and analyzing the model that uses PLSc-SEM (Partial Least Square Consistent-SEM) method. A consistent PLS approach came to the picture due to a considerable debate (controversy) about the credentials of the PLS algorithm itself. A specific school of thought expressed their reservations about PLS use in psychological research (Sarstedt et al., 2016). Many authors advocated for discontinuation of PLS (Rönkkö et al., 2016). At the same time, PLS found support in Rigdon (2016), who flagged the misconceptions about the conceptual base of using PLS. It was always meant for a composite-focused approach; hence, a formative model was conceived by default. Many studies used it just like CB-SEM (factor-based) and compared it with CB-SEM with pros and cons (Sarstedt et al., 2016; Kaufmann & Gaeckler, 2015; Rigdon, 2012; Hair et al., 2011). Henseler et al. (2016) provided two approaches in PLS: composite-based and factor-based. Amos (maximum likelihood) and Smart PLS (Consistent) methods provide almost similar results (Shmueli et al., 2016; Dijkstra and Henseler, 2015a,b). However, the actual confusion began after the introduction of Consistent PLS (Sarstedt et al., 2016; Dijkstra and Henseler, 2015a,b)) in an honest attempt to provide both composite and factor-based approaches in a single platform. It is high time to distinguish between factor-based and composite-based models and the relevant. The authors do not want to debate the reflective or formative nature of the relationships. Instead, the model should be clearly defined (PLS-SEM) or factor (CB SEM) and accordingly taken forward (Sarstedt et al., 2016). Keeping all these debates and technicalities aside, the authors have tried to compare all three methods (CB, PLS, and PLSc) with the same data. We tried to assess all these approaches with a reflective conceptual framework only. It is supported by many studies (Sarstedt et al., 2016; Kaufmann & Gaeckler, 2015; Astrachan et al., 2014; Rigdon, 2012;). However, the loadings did not change significantly with the formative approach. As mentioned already, PLS is best suited when composites are taken. In the next section, empirical evidence from consumer behavior research is undertaken to do the same.

6. Literature synthesis and empirical evidence

6.1. Literature review and hypotheses development

As the study's primary objective was to assess both SEM methods, our primary focus was not on the specific empirical data but its use in the comparative assessment. The items used in this study were adopted from prior studies (Dash et al., 2021). Nevertheless, the authors have briefly reviewed the existing literature related to the proposed hypotheses to benefit the readers.

6.1.1. Brand identity and customer satisfaction

"Brand identity is a unique set of brand associations that the brand strategists aspire to create or maintain. These associations represent what the brand stands for and imply a promise to customers from the organization" (Aaker, 1996). As a result, the brand's identity plays a massive role in enhancing the customer's satisfaction with the brand (Dash et al., 2021; Paul, 2019; Paul, 2015; Fennis & Pruyn, 2007; Carroll & Ahuvia, 2006;). Other researchers (Gilal et al., 2021; Gilal et al., 2020; Joshi & Garg, 2020; Ahearne *et al.*, 2005) supported this view. He had found that customer satisfaction is directly proportional to the enhanced brand identity. Based on the discussion above, it is proposed that:

H1: Brand Identity has a positive and significant impact on Customer Satisfaction.

6.1.2. Customer satisfaction and purchase intention

Customer satisfaction plays the role of an essential factor in the Marketing domain. It plays a massive role in influencing the purchase intention of prospective customers (Dash et al., 2021; Le-Anh and Nguyen-To, 2020; McQuitty *et al.*, 2000; Reichheld & Teal, 1996). If a customer is satisfied with the brand and its related components, her intention is strongly influenced, leading to a favorable decision. Based on the discussion above, it is proposed that:

H2: Customer Satisfaction has a positive and significant impact on Purchase Intention.

6.1.3. Brand identity and brand image

Brand image is defined as "largely a subjective and perceptual phenomenon that is formed through consumer interpretation, whether reasoned or emotional" (Dobni & Zinkhan, 1990). Therefore, it is generally considered as a mental picture that is subjective (Riezebos & Riezebos, 2003). A brand's identity typically shapes the image of the

brand. As it is subjective, the brand must work on its identity to provide a clear image to numerous customers (Dash et al., 2021). Based on the discussion above, it is proposed that:

H3: Brand Identity has a positive and significant impact on Brand Image.

6.1.4. Brand identity and purchase intention

A brand's identity is always considered to boost the customers' purchase intention and works as a linkage between marketers and customers (Temporal, 2006). It influences customer's preferences and loyalty, resulting in increased purchase intention (Dash et al., 2021; Prentice et al., 2020; Bruwer & Buller, 2012). Akin (2011) found that a brand's identity has numerous components that directly or indirectly affect the customer's purchase intention. Based on the discussion above, it is proposed that:

H4: Brand Identity has a positive and significant impact on Purchase Intention.

6.1.5. Customer satisfaction as a mediator

Customer satisfaction influences purchase intention (Rana & Paul, 2020; Tunçel and Özkan Tektaş, 2020; Paul, 2018). Similarly, brand identity influences purchase intention too. However, there is an indirect effect of identity on the purchase intention where customer satisfaction plays a mediator between the two ((Dash and Chakraborty, 2021); Barbić et al., 2019). Both direct and indirect effects need to be studied to assess the mediation effect. Customer satisfaction plays a good mediator between brand identity and purchase intention, providing a significant indirect effect (Dash et al., 2021; Shao et al., 2004; Blackwell et al., 2001). Based on the discussion above, it is proposed that:

H5: Customer Satisfaction mediates the relationship between Brand Identity and Purchase Intention.

A conceptual path diagram was developed accordingly that highlights all the hypotheses. (Figure 1).

6.2. Methodology

A case with actual primary data was discussed by using both methods that can be compared too. A sample of 466 respondents was taken, and a well-structured questionnaire with 16 items (questions) was developed. A five-point Likert scale was used to develop the items into statements where Strongly Disagree=1 and Strongly Agree=5. An online survey collected the data. Respondents from several countries, including India, Saudi Arabia, South Africa, the USA, and few other countries, participated in the survey. The banking, financial services, and insurance (BFSI) sector was chosen for the same. A hybrid sample design that included cluster and convenience sampling methods was implemented for the same. Data collection was done online in the last three months of 2020. The details of the respondents are provided in Table-2.

The items used in this study were adapted from earlier works of the authors. The collected information was first subjected to exploratory factor analysis (EFA) to get the factors first. EFA generated four factors with more than 78% variance explained. Next, as the responses were generally self-reported, we assessed the possible influence of common method bias (CMB). Finally, Harmon's one-factor test was applied to the data (Chakraborty et al., 2021; Podsakoff et al., 2003), and it was found that no dominating factor with more than 50% variance. In addition, unrelated marker variable method (Hair et al., 2010; Malhotra et al., 2006) was also used. Accordingly, the data were considered to be free from CMB.

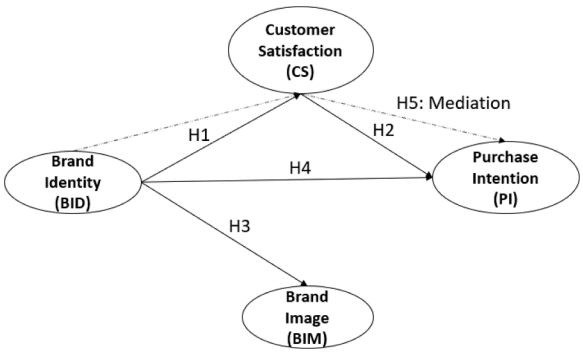


Fig. 1.. A Simple Conceptual Model.

These factors are named CS (Customer Satisfaction), PI (Purchase Intention), (BID) Brand Identity, and BIM (Brand Image). CS has five items: overall service quality, professional competence, satisfaction with the company, satisfaction with the product, and satisfaction with the front-line employee (cs1, cs2, cs3, cs4, and cs5) (Dash et al., 2021; Oliver, 2014; Mouri, 2005); PI has four items: willingness to buy, capability to buy, future intentions to buy, and repurchase decisions (pi1, pi2, pi3, and pi4) (Dash et al., 2021; Shao et al., 2004; Blackwell et al., 2001), the BID has four items: signage, sophistication, reputation, and reflection (bid1, bid2, bid3, and bid4) (Dash et al., 2021; Tsaur et al., 2016; Aaker, 1997); BIM has three items: mystery, sensuality, and intimacy (bim1, bim2, bim3) (Dash et al., 2021; Dash, 2018; Cho, 2011; Roberts, 2004).

This conceptual diagram is fed with empirical data, and both Amos and Smart PLS are used to analyze the same. First, the authors have used CB- SEM with the help of IBM® SPSS® Amos and then have verified with PLS-SEM with the help of Smart PLS.

6.3. CB-SEM (Amos)

CFA (Confirmatory Factor Analysis) was conducted to validate the constructs and their measurable indicators to confirm the EFA. CFA is conducted to test the EFA results with visualization and model fit. Once CFA is done, the final structural model between the four latent variables was tested with the empirical data. As the authors have discussed earlier, CFA verifies the measurement model, and SEM visualizes the path analysis of relationships among the factors. Once the CFA is conducted successfully, SEM is conducted (See Figure 2:). In a single structural relationship model, two phases are conducted. In the first stage, the items' loadings under the individual constructs are visualized. The relationships between the four factors (as per the conceptual model) are assessed in the second stage.

6.4. PLS-SEM (Smart PLS) and PLSc-SEM (Smart PLS)

Unlike Amos, Smart PLS is a tool based on partial least squares rather than covariance. The conceptual model discussed earlier is constructed in Smart PLS with the same dataset (See Figure 3:). Both the item loadings against the constructs and the relationships among the constructs are visualized in this model. Among all the options under the calculation feature, the authors have taken a simple PLS algorithm first. Many researchers consider a consistent PLS algorithm for a better structural relationship (Shmueli et al., 2016; (Dijkstra and Henseler, 2015a,b)). Therefore, the authors followed the simple PLS with a Consistent PLS algorithm (See Figure 4:). Nevertheless, it was found that the item loading is quite distinct from CB-SEM outputs.

6.5. Comparison

The outputs based on different parameters were compared first. Therefore, the comparison must be made with different angles and perspectives to avoid confusion.

6.5.1. Loadings of variables

First, the item loadings against the indicators were compared (See Table-3). All the items have a loading of more than 0.6, the widely accepted benchmark (Hair et al., 2010; Malhotra et al., 2006), except

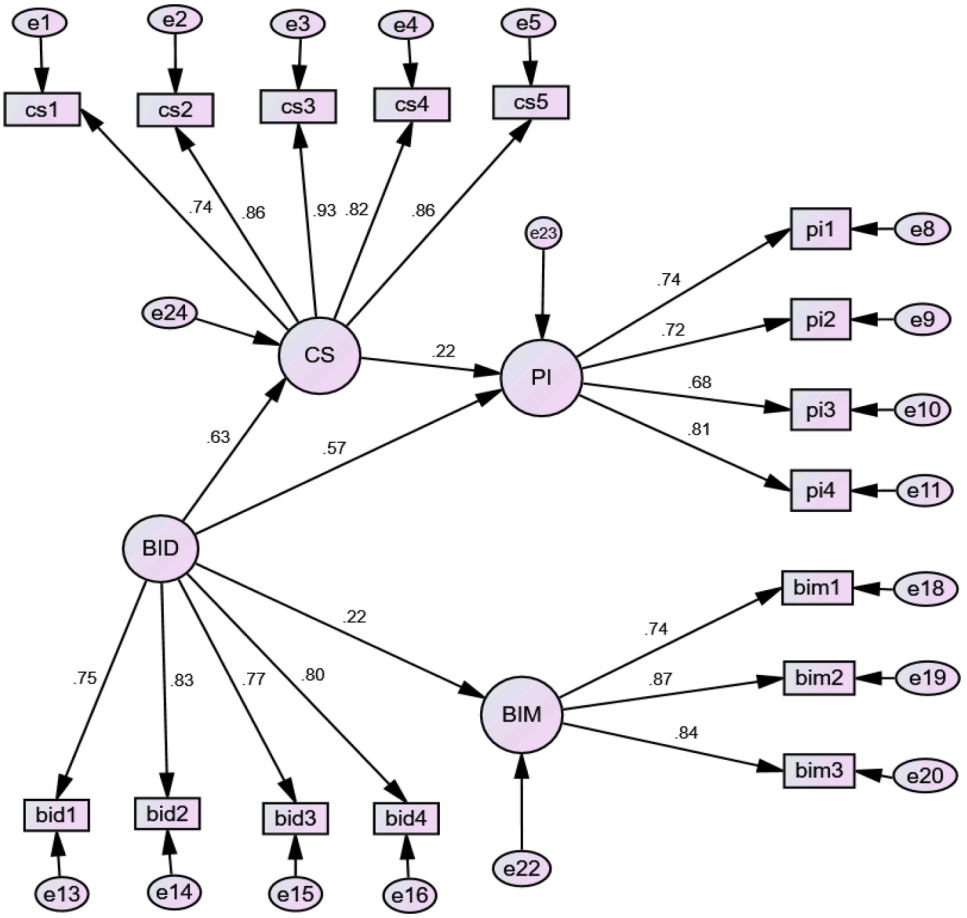


Fig. 2.. CB SEM (Maximum Likelihood).

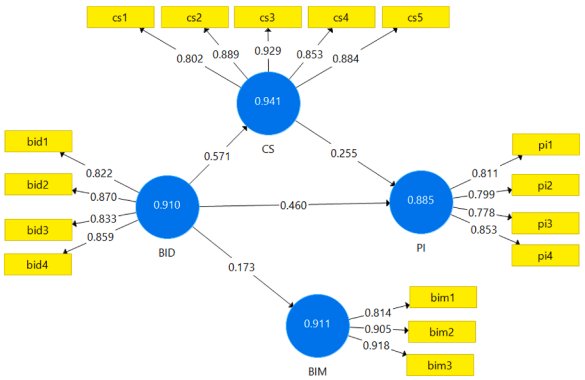


Fig 3.. SEM (PLS Algorithm). Note: Values in the Constructs are Composite Reliability (CR).

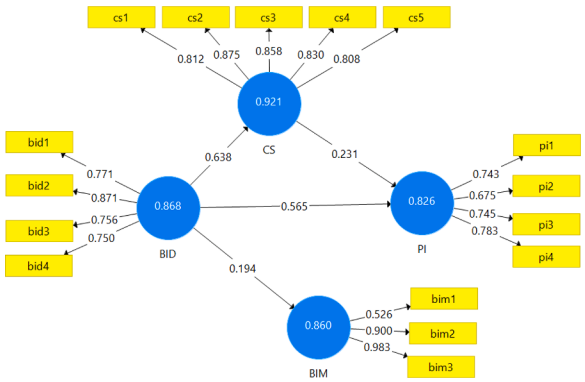


Fig 4.. SEM (Consistent PLS Algorithm) (PLSc). Note: Values in the Constructs are Composite Reliability (CR).

bim1 being 0.53 in PLSc-SEM. No items were dropped as the authors had already run pilot tests to filter the items. Previous studies (Hair Jr et al., 2017a) found that PLS-SEM retains almost everything, whereas the CB-SEM method needed few items to be dropped to improve the GoF indices. In this study, it was clear that the item loadings are usually higher in PLS-SEM than CB-SEM.

Furthermore, it was found that the range of loadings (between highest and lowest under one construct) was lower in PLS-SEM compared to CB-SEM. Hence, it can be concluded that the PLS method provides a more consistent item loading that boosts the reliability and validity of the factors. On the other hand, the loadings under PLSc-SEM did not provide any clear pattern. However, the loading for one item was

Table. 2
Details of the Respondents (No. of Respondents=466).

Category	Sub-Category	No of Respondents	Percentage
Gender	Male	285	61.2
	Female	181	38.8
Age (years)	Below (or equals) 35	321	68.9
	36 & above	145	31.1
Nationality	India	192	41.2
	Saudi Arabia	103	22.1
	South Africa	87	18.7
	USA	52	11.2
	Others	32	6.8

Table. 3
Loadings of Variables: CB-SEM vs. PLS-SEM vs. PLSc-SEM (Consistent).

Construct	Item	CB-SEM	PLS-SEM	PLSc-SEM (Consistent)
CS	cs1	.74	.80	.81
	cs2	.86	.89	.88
	cs3	.93	.93	.86
	cs4	.82	.85	.83
	cs5	.86	.88	.81
PI	pi1	.74	.81	.74
	pi2	.72	.80	.68
	pi3	.68	.78	.75
	pi4	.81	.85	.78
BID	bid1	.75	.82	.77
	bid2	.83	.87	.87
	bid3	.76	.83	.76
	bid4	.80	.86	.75
BIM	bim1	.74	.81	.53
	bim2	.87	.91	.90
	bim3	.84	.92	.98

very low (bim1). Therefore, on second thought, it can be said that except for one or two aberrations, PLSc provides a lower item loading compared to PLS and is closer to CB.

6.5.2. Relationship among constructs

The structural relationship between the constructs is compared in Table-4. There are four relationships in the SEM. The brand identity was found to be having a significant effect on customer satisfaction and purchase intention. It also has a substantial impact on brand image. Further, customer satisfaction has a significant impact on purchase intention. The findings are consistent with previous studies (Dash et al., 2021; Tsaur et al., 2016; Cho, 2011; Roberts, 2004; Aaker, 1997). Three relationships got higher values in CB-SEM, and one relationship got higher value (CS → PI) in PLS-SEM. Hence, nothing is conclusive to pick the better method. Few researchers have always maintained that the structural relationship is closer to CB-SEM if a consistent PLS algorithm is undertaken in PLS-SEM (Shmueli et al., 2016; Dijkstra and Henseler, 2015a,b). The authors found the same result in this study (See Table-4). Although not surprising, the relationships under CB and PLSc provided almost similar, if not identical, results. However, the indicator reliability and validity go down in a consistent PLS algorithm compared to PLS.

6.5.3. Factor validity and reliability

Before the structural model and the relationship, the four constructs were tested for reliability and validity (See Table-5). Constructs must have an AVE value of at least 0.5 as per the criterion, and it is met (Hair Jr et al., 2017a; Fornell & Larcker, 1981). Fornell- Larcker criterion (1981, 2006) was considered for the same. For CR values, the suggested threshold is 0.8. The result shown in Table-5 meets the requirements reflecting that an internal consistency exists, indicating the reliability of these values.

Further, for all the constructs, AVE values were greater than the respective MSV values. In this study, there is a pattern found. Although AVE is greater than 0.5 and CR is greater than 0.8, PLS-SEM produced higher values than CB-SEM in both methods. The AVE values were comfortably more than 0.6, and the CR values were almost 0.9 and above in the PLS-SEM method. However, PLSc produced lower values for both AVE and CR. Nevertheless, the values were almost similar to the values obtained in CB. Hence, it can be concluded that PLSc and CB provide similar outcomes regarding construct reliability and validity.

Table. 4
Relationship Among Constructs:**CB-SEM vs. PLS-SEM vs. PLSc-SEM (Consistent).**

Relationship/ Hypotheses	CB-SEM	PLS-SEM	PLSc-SEM (Consistent)
BID → CS	.63**	.57**	0.64**
CS → PI	.22**	.26**	0.23**
BID → BIM	.22**	.17**	0.19**
BID → PI	.57**	.46**	0.57**

*significant at 5%**significant at 1%

Table. 5
Factor Validity and Reliability: CB-SEM vs PLS-SEM vs PLSc-SEM (Consistent).

	CB-SEM		PLS-SEM		PLSc-SEM (Consistent)	
	AVE	CR	AVE	CR	AVE	CR
BID	.62	.87	.72	.91	.62	.87
BIM	.67	.86	.78	.91	.69	.86
CS	.71	.92	.76	.94	.70	.92
PI	.55	.83	.66	.89	.54	.83

6.5.4. Model fit indices

The path analysis was conducted through a structural model that must be tested for model fit. In CB-SEM, there are many features to test the same. Many fitness measures were introduced mainly to assess and compare the results of LISREL (Lohmöller, 1989). Although these measures are useful for CB, they are not entirely helpful in correctly assessing model fit in PLS.

PLS-SEM lacks in this aspect as the concept behind the method is different. PLS-SEM literature is still evolving in this aspect, and it is cautioned not to report the model fit indices to conclude anything (Hair Jr et al., 2017a). CB-SEM is usually used for theory testing that needs a detailed model fit assessment to validate the same.

Model fit indices in PLS offer limited options compared to CB. Few approximate measures like SRMR, NFI, and Chi^2 are provided. Exact measures like d_ULS (i.e., the squared Euclidean distance) and d_G (i.e., the geodesic distance) are also provided by PLS (Dijkstra and Henseler, 2015a,b). Almost all the GoF measures meet the threshold level set by previous literary works (See Table-6). For CB-SEM, AGFI is a bit lower than the benchmark (0.89). GFI seems good (0.92) and NFI (.93) & CFI (.95) are above the cut-off marks. SRMR is at 0.4 and RMSEA is at 0.7.. In this study, PLS-SEM has reported SRMR at 0.06 and NFI at 0.89. PLSc reported better SRMR compared to PLS (0.05), indicating a better model fit. Both d_ULS (i.e., the squared Euclidean distance) and d_G (i.e., the geodesic distance) offer values that are not significant, indicating a good model fit (for both PLS and PLSc) (Hair Jr et al., 2017a; Hair Jr et al., 2017b; Dijkstra and Henseler, 2015a,b). There is no clarity about choosing values of saturated and estimated models, but many researchers have suggested estimated model values for these measures in PLS (Hair Jr et al., 2017a; Hair Jr et al., 2017b; Dijkstra and Henseler, 2015a,b). These findings should be ignored compared to CB-SEM, which is quite exhaustive. Model fit indices must be taken together to assess the model, not individually, to have a better perspective.

6.5.5. Mediation and moderation (Interaction)

There are two more aspects, which can be discussed with this empirical data. First, the mediation effect can be discussed. In this study, the model has one mediation effect: BID→CS→PI. Customer Satisfaction acts as a mediator between brand identity and purchase intention. To examine the significance of indirect effects, bootstrapping technique was applied that fixes no importance on the normality of data distribution (Preacher & Hayes, 2008) and determines mediation effects

Table. 6
Model Fit Indices: CB-SEM vs. PLS-SEM vs. PLSc-SEM.

	CB-SEM	PLS-SEM	PLSc-SEM
Chi-square of the estimated model	**	**	**
GFI	.92	–	–
AGFI	.89	–	–
NFI	.93	.89	.87
CFI	.95	–	–
TLI	.94	–	–
RMSEA	.07	–	–
SRMR	.04	.06	.05
d_ULS	–	.58	.41
d_G	–	.23	.29

(Byrne, 2013). When both direct and indirect effects are significant, partial mediation is anticipated (Shankar et al., 2020; Cheung & Lau, 2008). In this study, both methods give similar results. Although direct effects were different (same in the consistent PLS), indirect effects were the same. As both the effects were significant, the mediation effect was considered partial (See Table-7).

Secondly, the moderation effect can be compared in these two methods. The authors have not taken moderation in this study. PLS-SEM can provide an apparent moderation (interaction effect) with good visualization, whereas CB-SEM (Amos) demands more from the researchers. It needs a standardization or normalization approach to calculate the interaction effect. The 'PROCESS macro for SPSS, SAS, and R' is another good tool for assessing the same.

7. General discussion

Talking about our empirical data used in this study, it can be concluded that purchase intention is hugely affected by brand identity. Brand image is dependent on brand identity. Customer satisfaction plays a significant role in boosting purchase intention too. All the five hypotheses set in this study are accepted in all three methods. After going through these three cases, one should be able to draw inferences out of the outputs. Both the applications provide two interfaces. The first is the path diagram for visualization and presentation purposes, whereas the other provides reporting purposes. Rather than compare both, one needs to choose one of these as per the need of the research. CB-SEM and PLS-SEM can be discussed in general rather than the specified tools used in this study. There are numerous aspects of research, and each element might be unique too. Usually, CB-SEM demands a lot from the data, whereas PLS-SEM is quite lenient in this aspect. It requires the data must be normal, the sample must be large, etc. (Astrachan et al., 2014). There are many highly critical voices of PLS usage (Rönkkö et al., 2016), and even few advocated for discontinuation (Antonakis et al., 2010). However, PLS found strong support from many researchers (Rigdon, 2016; Sarstedt et al., 2016; Astrachen et al., 2014).

Further, to be specific, if the researchers' primary objective is to estimate a factor-based model, CB-SEM is the preferred one. On the other hand, if the primary aim is to estimate a composite-based model, PLS-SEM should be considered. Sometimes, a mixed model might be the need of the researcher. A consistent PLS algorithm can be considered for the same (Rigdon et al., 2017; Dijkstra and Henseler, 2015a,b). Although our selection of items was refined through pilot testing, major studies concluded that PLS-SEM retains more measurement items under the constructs than CB-SEM (Astrachan et al., 2014). As discussed, there might be many experimental expeditions with different configurations to reach the best model in the theory development stage. CB-SEM does not support this as one is stuck with a factor-based approach. PLS-SEM can provide this opportunity (Rigdon et al., 2017; Wold, 1974). Furthermore, PLS-SEM can be used for prediction and explanation, whereas CB-SEM is limited to explanation (Hair Jr et al., 2017a; Wold, 1974). The most significant advantage of PLS-SEM is that both formative and reflective measurement models can be specified with it, whereas CB-SEM is limited to reflective models only.

Furthermore, it can handle non-metric data (Rigdon et al., 2017; Hair Jr et al., 2017a; Wold, 1974). Recently, two studies highlighted the advantage of PLS in handling two significant concepts of SEM: Mediation Analysis and Confirmatory Factor Analysis (CFA). Previous studies had always emphasized the limitations posed by regression methods. The composite-based model provides the solution to complex mediation models. Moreover, it overcomes the limitations of both factor-based and regression methods (Sarstedt et al., 2020). A new alternative approach to CFA was proposed, known as Confirmatory Composite Analysis (CCA) (Hair Jr et al., 2020). With the help of PLS-SEM, the measurement model can be confirmed with the composites themselves. Thus, it has numerous advantages over other methods. New measures can be developed too by this method. It can handle both reflective and formative models as per the needs.

In this study, it was found that both methods are equally effective for developing the structural relationship. The study had a large sample size (466); hence both ways were similarly effective. Even though the items were refined by pilot testing and the factors are pre-conceived, PLS-SEM too provided the same constructs as CB-SEM. Further, it can be said that both the methods are efficient, provided the data is refined and normal. Most of the authors have used CB-SEM more than PLS-SEM. However, after going through this empirical analysis and the latest literature, it can be said that PLS-SEM provides more flexibility to explore and experiment with numerous configurations.

7.1. Improving model fit in SEM

Though our target is to achieve the model fit, there are many instances (mainly primary data) where the model fit is poor. It can happen due to many things, e.g., the complexity of the model or sample size and quality. There are many ways to improve the same. Checking the factor loadings of the indicators on the latent variable is the first choice. The items with factor loading less than 0.6 can be dropped, and the model fit is reassessed (Mueller & Hancock, 2018; Hayes et al., 2017). If the model fit is still not achieved, the modification should be attempted. This happens because some items are redundant (highly correlated and similar in their meaning). This problem can be solved by using modification indices to check high levels. Modification indices (M.I.) search for a high M.I. between the indicators and the error terms, and it is shown pairwise. Once the redundancy is found, there are two ways to solve it. First, one of the redundant items can be dropped. Second, both the indicators/ error terms can be used as a free parameter using covariance (Hair et al., 2010; Hair Jr et al., 2020). Nevertheless, one thing must be kept in mind, i.e., the underlying theory behind the model. We should focus on fitness indices and improve them but rather go back to the data, sample, methods, etc., for real answers.

8. Limitations and future research

8.1. Limitations

Although the authors have tried to incorporate all the significant aspects and perspectives while conducting this study, few limitations must be noted. First, the model considered was a simple one to keep the explanations to the bare minimum. The complex model was not considered that could have explained few more differences. Second, the sample size could be raised to a minimum of 1000 with diverse respondents to get a better picture. Third, demographic and socio-economic factors as control variables are ignored in this study as it was not our objective. Fourth, the specified model used in this study was not composite-based. Still, regular PLS was used to assess it, which might not be a good idea. However, the authors continued with it because of enormous literary support for the same.

Furthermore, PLSc was explicitly used to counter this issue. Finally, only two software packages from each approach were taken; more competing packages could have been included to assess comprehensively. The authors hope that the mentioned limitations will provide considerable insights to other researchers for future works.

Table. 7
Mediation Effects: CB-SEM vs. PLS-SEM vs. PLSc-SEM (Consistent).

Hypothesis		Direct effect	Indirect effect	Result
BID→CS→PI	CB-SEM	.57**	.14**	Partial
	PLS-SEM	.46**	.15**	Partial
	PLSc-SEM	.57**	.15**	Partial

*significant at 5%**significant at 1%

8.2. Directions for future research

Following Paul & Mas (2020), we provide detailed directions for future research in different fields in this section. This SEM software is beneficial in research in the management of technology, forecasting of technology adoption, and in different areas of social science research. Numerous literary works always supported SEM as an effective tool in technology forecasting (Staphorst et al., 2014). Various technology-based measurements can be used as indicators to forecast the need for a specific technology to be employed. An SEM can be developed, and with empirical data from technology users, the technology commercialization success can be forecast (Sohn & Moon, 2003). With a good knowledge of the various factors affecting the technology, such as type, utility, and competitive advantage, the success of technology can be forecast. The factors can be used as measurement indicators, and with the help of SEM, they can be predicted easily (Staphorst et al., 2014; Lasserre, 1982). First, a conceptual framework is developed, and then SEM is constructed. Once the measurement indicators are finalized from the data, the technology can be predicted. Although both CB-SEM and PLS-SEM can be used in technology forecasting, PLS has an edge as it is lenient compared to maximum likelihood (ML) requirements (Fornell et al., 1996). In addition, PLS quickly estimates the cause-and-effect relationships (complex). Therefore, forecasting a technology needed for a specific set of customers can be easily estimated with the affecting factors derived from the customers. SEM in technology forecasting-related research is enormous, particularly related to the customers and their needs (Fornell et al., 1996).

Future researchers could use the insights from this article in three different ways: theory development, theory application, and comparison of complex models. Some recommendations for future research can be made as follows in this domain. First, composite-based models should be tested with both methods to assess their efficacies. In the future, SEM will see more composite-based models compared to factor-based (Sarstedt et al., 2016). Second, a complex consumer behavior research relationship can be tested with both approaches to have a fair and healthy comparison. More antecedents and consequents with few control variables can be explored. Third, moderation effects were not considered in this study. It is one of our limitations too. Few advanced and complex model structures with moderation effects can be used. Finally, specific consumer behavior domains can be taken, and a comparative assessment can be conducted.

9. Conclusion

We can see those complex models, especially multiple regression models (simultaneously) with direct and indirect effects among latent variables, are easily explained by SEM. We have discussed only two popular and widely used software in this study. Software is not essential; understanding the concept and logic behind using SEM is most crucial. It is more of a confirmatory study than exploratory (CB-SEM); hence underlying theories are critical. Model specification is necessary, to begin with. Then, model estimation is attempted with available data, and finally, the model is validated with statistical tools. Usually, it analyses how close is estimated values are to the observed values with the help of the measurement model and the path model. Path coefficients provide the degree of impact on the dependent constructs and explain the conceptual model.

Finally, the entire study can be summarized before concluding. Each latent construct is clearly defined before developing the measurement model for the constructs. The whole measurement model is assessed for normality, reliability, and validity. Unidimensionality and Discriminant validity for the measures are undertaken along with composite reliability. Further, all the model fit indices must suffice (Absolute, Incremental, and Parsimonious). Once the measurement is validated, the final structural path model is developed. PLSc is closer to CB than PLS, although the reflective vs. formative relationship is not entirely answered by it. There is no single way to excellence. CB or PLS or PLSc do not matter. The underlying theories are crucial for choosing a method. Composite-based models should opt for PLS, whereas factor-based models should use CB or PLSc. As per the conceptual model (based on theory), the constructs are connected. Once again, the path model is assessed for model fit and compared with similar models. Accordingly, conclusions can be drawn, and necessary steps can be taken. Other empirical datasets must be tested to find out universal outcomes.

Note: In this study, the authors have used IBM® SPSS® Amos version 24 and Smart PLS 3.3.3 for comparative analysis. The authors have no conflict of interest related to both packages.

CRediT authorship contribution statement

Ganesh Dash: Conceptualization, Methodology, Software, Writing – original draft. **Justin Paul:** Investigation, Supervision, Validation, Writing – review & editing.

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