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PLS-SEM or CB-SEM Method for Customer Loyalty Towards Mobile Service Providers Data

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Abstract

This study compares two commonly used Structural Equation Modeling (SEM) methods—Partial Least Squares SEM (PLS-SEM) and Covariance-Based SEM (CB-SEM)—to assess customer loyalty data in the telecommunications industry. The comparison was conducted using a dataset of 448 mobile service users in Melaka, where service providers have faced challenges in meeting performance standards. Findings reveal that PLS-SEM outperforms CB-SEM in terms of Average Variance Extracted (AVE) and Composite Reliability (CR), with AVE values exceeding 0.68 compared to CB-SEM's 0.58, and CR values above 0.89 compared to CB-SEM's 0.84. These results highlight PLS-SEM’s superior construct reliability and validity, particularly for complex models and smaller sample sizes. This study provides valuable insights into selecting appropriate SEM techniques for customer loyalty research.

Keywords: PLS-SEM, CB-SEM, customer loyalty, telecommunications, construct validity.

INTRODUCTION

Structural Equation Modelling (SEM) is a multivariate analysis method with two main approaches: Covariance-Based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM) (Hair et al., 2021). CB-SEM is primarily used for theory confirmation and analyzing the relationships between latent and observed variables, while PLS-SEM is more suitable for prediction and analyzing relationships between latent constructs (Ahmed et al., 2024; Hair et al., 2021). PLS-SEM offers advantages in handling small datasets, high measurement error, and unbalanced data (Ahmed et al., 2024). Comparative studies show that PLS-SEM often produces higher composite reliability, convergent validity, and explained variance in dependent variables (Hair et al., 2017; Ali et al., 2017). However, both approaches have specific strengths and limitations, and the choice between them depends on factors such as research objectives, dataset characteristics, and available resources (Ahmed et al., 2024; Hair et al., 2021).

PLS-SEM has emerged as a valuable alternative to covariance-based SEM in marketing and social science research. Hair et al. (2011) first introduced PLS-SEM as a "silver bullet" for estimating causal models in various theoretical and empirical situations. Subsequent research has refined and expanded this perspective. Sarstedt et al. (2022) provided updated insights on the original paper, addressing criticisms and ambiguities. Hair et al. (2019) offered guidance on when to use PLS-SEM, discussing model evaluation metrics, and emphasizing methodological extensions to enhance analysis quality. The flexibility of this method in handling small sample sizes, complex models, and formative constructs has contributed to its growing popularity across various disciplines (Fong & Law, 2013). As PLS-SEM evolves, researchers are encouraged to consider the latest developments and guidelines when using or evaluating PLS-SEM-based research (Hair et al., 2019).

On the other hand, CB-SEM is a robust statistical technique for model confirmation and theory development in social sciences, particularly in marketing (Hair et al., 2014). It requires large sample sizes, typically more than 200 subjects (Tenenhaus, 2007). CB-SEM is complemented by component-based SEM approaches like PLS-SEM, which can be used with smaller samples (Tenenhaus, 2008). Both methods have been applied in advertising research, contributing to conceptual and methodological advancements in the field (Hair et al., 2017). CB-SEM is especially useful for studying complex relationships between multiple constructs and modeling higher-order constructs (Hair et al., 2014). While CB-SEM and PLS-SEM have distinct strengths, research shows that the calculation of scores and bootstrap validation results are often insensitive to the choice between these methods when dealing with homogeneous data blocks (Tenenhaus, 2008). Researchers should consider their specific objectives and sample sizes when choosing between CB-SEM and component-based approaches.

Structural Equation Modeling (SEM) is a robust statistical approach for analyzing relationships among latent and observed variables. It is widely employed in marketing and management research to evaluate theoretical models and validate constructs. Two primary SEM approaches are Covariance-Based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM) (Hair et al., 2021). While CB-SEM excels in theory testing due to its emphasis on model fit indices such as CFI and RMSEA, PLS-SEM is preferred for predictive modeling and exploratory research, particularly when dealing with smaller sample sizes or complex constructs. Both methods have strengths and limitations, making the choice context-dependent based on research objectives and dataset characteristics.

This study examines the relevance of PLS-SEM and CB-SEM in evaluating customer loyalty within the telecommunications sector. Customer loyalty is a critical metric for service providers, particularly in Melaka, where mobile service satisfaction has been suboptimal. This region serves as a compelling case study due to its diverse consumer base and the ongoing challenges faced by service providers in meeting customer expectations. Insights gained here can inform strategies applicable to similar competitive markets globally. Analyzing customer loyalty in this context is crucial as it provides insights into retaining customers in a highly competitive market.

The study addresses the following research questions:

1. Which SEM method provides superior construct validity and reliability?
2. How do PLS-SEM and CB-SEM differ in their capacity to model customer loyalty constructs?

The novelty of this study lies in its direct comparison of PLS-SEM and CB-SEM using a real-world dataset from the telecommunications sector, an area with limited existing comparative research. Unlike prior studies that focus on general SEM applications, this research specifically addresses the unique methodological challenges and practical implications of assessing customer loyalty in a dynamic and competitive market like Melaka. It bridges the gap between theoretical advancements in SEM techniques and their practical applications in understanding consumer behavior. By focusing on Melaka, this research also highlights regional challenges that may resonate with similar markets globally.

LITERATURE REVIEW

Structural Equation Modelling (SEM) has gained significant popularity in research areas such as Information Systems (IS). Gefen et al. (2000) provided guidelines for selecting the appropriate SEM technique, comparing covariance-based SEM and PLS-based SEM, and offering heuristics for their use. The growing use of SEM in IS research is evident, with more than 90% of applications occurring after 1994 (Im & Grover, 2004). Despite its increased acceptance, SEM remains complex and challenging to apply effectively. Ringle et al. (2012) examined the use of PLS-SEM in IS, identifying potential problem areas and emphasizing the importance of adhering to established reporting standards.

Structural equation modeling (SEM) offers two main approaches: covariance-based (CB-SEM) and partial least squares (PLS-SEM). CB-SEM is primarily used for theory confirmation and analyzing complex latent and manifest constructs (Hair et al., 2021; Ahmed et al., 2024). PLS-SEM, on the other hand, is more suitable for prediction, handling small datasets, and analyzing relationships among latent constructs with high measurement error (Ahmed et al., 2024; Hair et al., 2021). Comparative studies have shown that PLS-SEM often requires fewer indicator removals to achieve acceptable model fit and demonstrates higher composite reliability and convergent validity than CB-SEM (Hair et al., 2017). However, both approaches yield similar results in terms of discriminant validity and beta coefficients (Hair et al., 2017; Amaro et al., 2015). The choice between CB-SEM and PLS-SEM depends on factors such as research objectives, dataset characteristics, and available resources (Ahmed et al., 2024; Hair et al., 2017).

There are few studies that compared PLS-SEM and CB-SEM, such as Hair et al. (2017), which provides guidelines on when to use each method, emphasizing their strengths in exploratory and confirmatory analyses. Afthanorhan (2013) offers a practical comparison in confirmatory factor analysis, while Richter et al. (2014) discusses the methodological differences relevant to international business research. Mia et al. (2019) examines CB-SEM's performance in management research, contrasting it with PLS-SEM. Additionally, Sarstedt et al. (2022) analyzes the evolution of PLS-SEM in marketing research, addressing criticisms and advancements.

Recent comparative analyses have provided a deeper understanding of the strengths and limitations of both techniques. Richter et al. (2014) emphasized the advantages of PLS-SEM in modeling complex and formative constructs, noting its efficiency in exploratory scenarios where theory is less established. In contrast, CB-SEM is preferred for studies aiming to confirm predefined models due to its rigorous validation processes. Despite these insights, there remains a need for systematic comparisons of PLS-SEM and CB-SEM in specific domains, such as the telecommunications sector. Existing studies often focus on general applications, leaving domain-specific nuances underexplored.

This study contributes to the ongoing debate on the suitability of PLS-SEM and CB-SEM by showcasing their applicability to different types of datasets and research objectives. Through the analysis of customer loyalty data from the telecommunications sector, it demonstrates how PLS-SEM excels in handling smaller sample sizes and complex constructs, while CB-SEM proves advantageous for confirmatory analysis with well-structured datasets. The findings provide practical insights into selecting appropriate SEM methods based on specific research contexts, bridging the gap between theoretical advancements and their practical applications in real-world scenarios. Specifically, this research illustrates the practical implications of using PLS-SEM for smaller sample sizes and complex constructs, as well as CB-SEM's strengths in theory testing with well-structured datasets. By applying these methods to a real-world telecommunications dataset, the study provides empirical evidence that informs methodological choices based on specific research contexts.

Service quality, trust, customer satisfaction, and corporate image have been identified as significant antecedents of customer loyalty (Aydin & Özer, 2005; Akbar & Parvez, 2009). Research using SEM shows that trust and customer satisfaction have a positive effect on loyalty, with satisfaction mediating the relationship between perceived service quality and loyalty (Akbar & Parvez, 2009). Furthermore, customer engagement and commitment have been found to have a positive relationship with loyalty (Dhasan et al., 2017). Research suggests that mobile operators need to focus on differentiating their services and ensuring quality to maintain competitiveness (Aydin & Özer, 2005). Additionally, promotional offers have been found to have a significant relationship with customer engagement and commitment (Dhasan et al., 2017). These findings highlight the importance of understanding and managing various factors to build and maintain customer loyalty in the mobile telecommunications sector.

METHODOLOGY

This study utilizes secondary data collected from a survey of 448 mobile service users in Melaka. The data was obtained from previous research study, ensuring access to a pre-existing dataset with comprehensive information on customer perceptions of service quality, satisfaction, trust, and loyalty. The dataset was selected for its relevance to the study objectives and its robust design, which aligns with the requirements for Structural Equation Modeling (SEM) analysis. Structural Equation Modeling (SEM) often requires a minimum sample size to ensure reliable parameter estimation. Common rules of thumb suggest 10-20 respondents per parameter or indicator in the model. If the study involves 20-40 parameters, the sample size of 448 exceeds these recommendations, providing robust power for detecting significant relationships.

In measuring reliability and validity using both PLS-SEM and CB-SEM methods, several metrics such as loadings, Average Variance Extracted (AVE), and Composite Reliability (CR) will be tested. For this study, a reflective measurement model will be used. A reflective measurement model must be evaluated for reliability and validity to ensure consistency. Reflective measurement models were evaluated using item loadings, AVE, and CR. A loading threshold of 0.50 was chosen as it indicates that an item explains at least 25% of the variance in its corresponding construct, providing a balance between retaining meaningful indicators and ensuring the model's validity. Loadings below 0.50 were excluded to maintain unidimensionality, as they suggest weaker relationships between items and constructs, potentially compromising reliability and validity.

Construct reliability can be classified as composite reliability. According to Zainudin (2012), reliability refers to the extent to which the measurement model reliably measures the intended latent construct. Unlike Cronbach's alpha proposed by Nunally and Bernstein (1994), values greater than 0.70 indicate that the measurement model is reliable. Composite reliability values between 0.60 and 0.70 are acceptable in exploratory research, and values from 0.70 to 0.90 in more advanced research stages are considered satisfactory (Nunally and Bernstein, 1994), while values below 0.60 indicate a lack of reliability.

Unidimensionality is achieved when measurement items have acceptable loadings for their respective latent constructs. Item loadings refer to the strength of the relationship between an item (indicator) and the construct (factor). In SEM, higher item loadings indicate that the item has a strong relationship with the construct it represents. Generally, item loadings above 0.7 are considered good because they indicate that the item explains more than 50% of the variance in the construct (Hair et al., 2016). ndicators with loadings between 0.40 and 0.70 may be retained if they are theoretically justified, especially if removing them reduces content validity.

For convergent validity, the AVE (Average Variance Extracted) value is used to measure the amount of variance extracted by the construct compared to the variance not explained by the construct's items. Higher AVE values suggest that the construct has better explanatory power. According to Hair et al. (2016) and Fornell & Larcker (1981), AVE values greater than 0.5 are considered satisfactory, as they indicate that more than 50% of the variance in the construct's items is explained by the construct itself.

$$\text{AVE} = \frac{\text{Sum of the squared standardize loadings}}{\text{Sum of the squared standardize loadings} + \textit{measurement error}}$$

$$\text{Measurement error} = 1 - (\text{standardized loadings})^2$$

Figure 1: Average Variance Extracted (AVE)

Composite Reliability (CR) is a measure of construct reliability that assesses the extent to which items within the construct are consistent in measuring the same construct. A CR value higher than 0.7 indicates that the construct has good reliability, which is important to ensure that the measures used are consistent and reliable (Hair et al., 2016). CR values between 0.60 and 0.70 in exploratory research and values from 0.70 to 0.90 in more advanced research stages are considered satisfactory (Nunally & Bernstein, 1994), while values below 0.60 indicate a lack of reliability.

$$\text{CR} = \frac{\text{Squared of the sum of standardized loadings}}{\text{Squared of the sum of standardized loadings} + \textit{measurement error}}$$

Figure 2: Composite Reliability (CR)

This study aims to evaluate which software is most suitable for conducting confirmatory factor analysis through the use of SMARTPLS and AMOS. Each application has different functions. For example, SMARTPLS was developed for PLS-SEM. Although there are many other applications for analyzing this method, SMARTPLS is the most widely used and is more efficient with appealing graphics. Meanwhile,

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AMOS has been designed for CB-SEM and has been in use since 2004. Therefore, the study's objective should be achieved by utilizing both of these software applications.

FINDINGS AND DISCUSSION

In this study, a comparative analysis between Partial Least Squares SEM (PLS-SEM) and Covariance-Based SEM (CB-SEM) was conducted to assess the effectiveness of both methods in measuring customer loyalty data towards mobile service providers.

Measurement Model for PLS-SEM

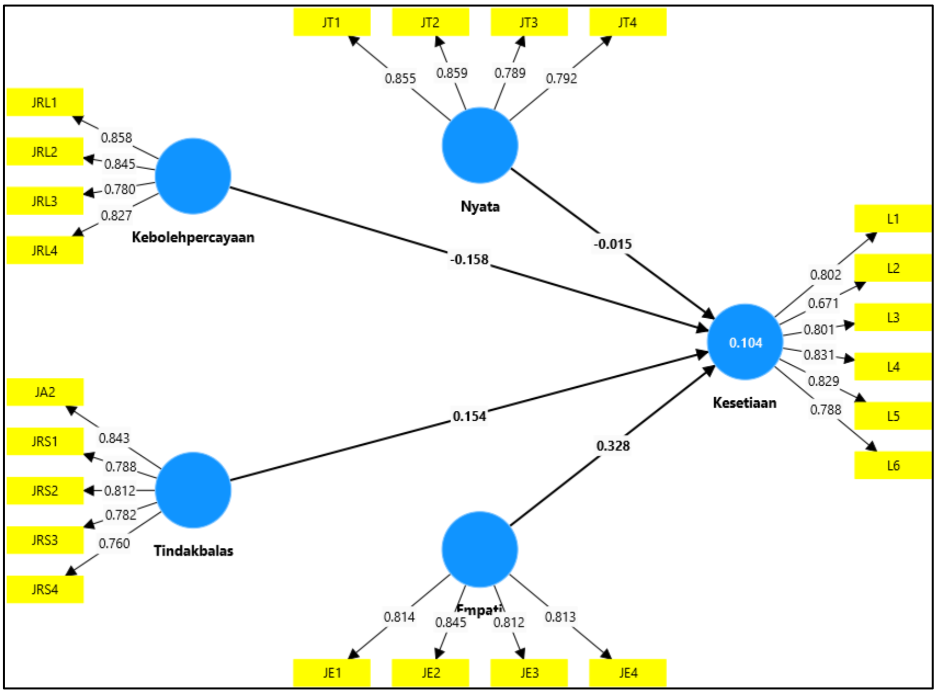

Figure 3 Outer Loadings after unidimensionality procedure (PLS-SEM).

Table 1 Loadings after unidimensionality procedure (PLS-SEM)

Nyata	Loadings	*Keboleh percayaan*	Loadings	*Tindak balas*	Loadings	*Empati*	Loadings	*Kesetiaan Pelanggan*	Loadings
JT1	0.855	JRL1	0.858	JRS1	0.788	JE1	0.814	L1	0.802
JT2	0.859	JRL2	0.845	JRS2	0.812	JE2	0.845	L2	0.671
JT3	0.789	JRL3	0.780	JRS3	0.782	JE3	0.812	L3	0.801
JT4	0.792	JRL4	0.827	JRS4	0.760	JE4	0.813	L4	0.831
								L5	0.829
								L6	0.788

The figure and table above display the measurement model based on findings from SMARTPLS. These values are obtained from the outer loadings, which indicate the loading of each indicator on the factors involved. From the beginning of the study, the researcher proposed that loadings of 0.50 or higher should be retained in the measurement model. Therefore, outer loadings below 0.50 should be removed from the measurement model, as they indicate that the indicator contributes less to the factors. In this case, no items have been removed from this latent factor. This procedure is known as the unidimensionality procedure. After this process is completed by the researcher, the model needs to be evaluated to improve its reliability and validity. Thus, convergent validity is applied in this process. Additionally, construct reliability or composite reliability should also be tested.

Table 2 Convergent Validity and Construct Reliability (PLS-SEM)

Variables	Average Variance Extracted (AVE)	Composite Reliability	Cronbach's alpha	Communality
Nyata	0.680	0.894	0.860	0.680
Kebolehpercayaan	0.684	0.915	0.911	0.686
Tindakbalas	0.656	0.897	0.872	0.636
Empati	0.674	0.892	0.847	0.674
Kesetiaan Pelanggan	0.623	0.908	0.901	0.622

The table above presents the results for AVE and composite reliability. Additionally, internal reliability, represented by Cronbach's alpha, is also shown as a traditional method for determining the reliability of the measurement model. Therefore, this method remains necessary to assist researchers in obtaining an accurate model. According to Fornell and Larcker (1981), AVE is acceptable when its value is greater than 0.50. Moreover, Nunally (1978, 1994) recommends a value greater than 0.70 for composite reliability and Cronbach's alpha. Furthermore, some researchers require Communality to determine the acceptance of the measurement model. According to Gaskin (2012), Communality values are acceptable when they exceed 0.50. Thus, all requirements for convergent validity, composite reliability, Cronbach's alpha or internal reliability, and Communality have been met.

Measurement Model for CB-SEM

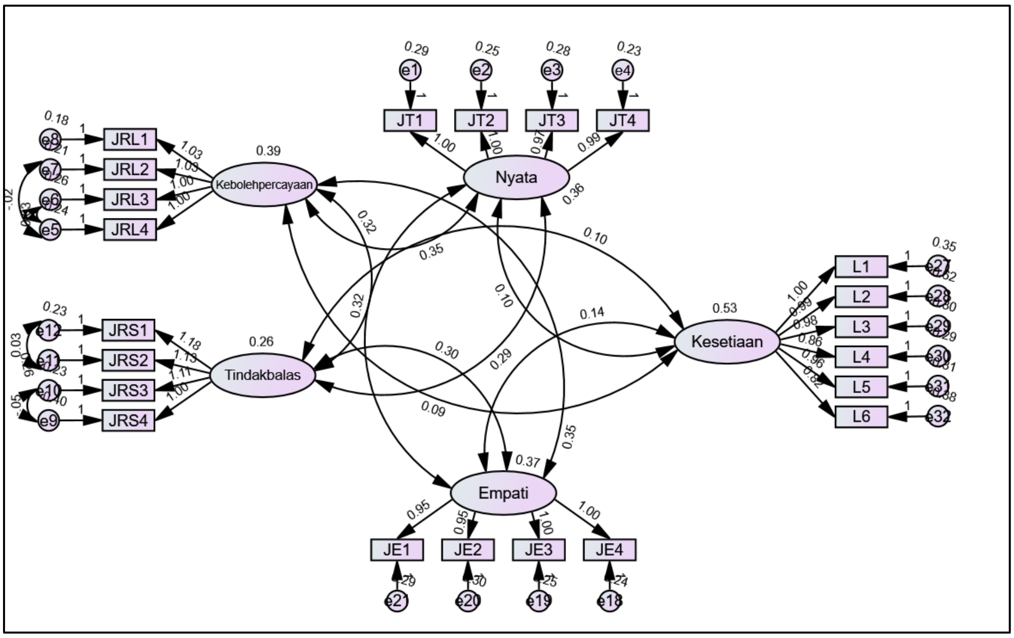

Figure 4 Outer Loadings after unidimensionality procedure (CB-SEM).

Table 3 Loadings after unidimensionality procedure (CB-SEM)

Nyata	Loadings	*Kebolehpercayaan*	Loadings	*Tindak balas*	Loadings	*Empati*	Loadings	*Kesetiaan Pelanggan*	Loadings
JT1	0.743	JRL1	0.837	JRS1	0.793	JE1	0.732	L1	0.776
JT2	0.766	JRL2	0.807	JRS2	0.762	JE2	0.726	L2	0.672
JT3	0.742	JRL3	0.778	JRS3	0.763	JE3	0.774	L3	0.795
JT4	0.780	JRL4	0.790	JRS4	0.621	JE4	0.780	L4	0.756
								L5	0.781
								L6	0.691

The figure and table above display the factor loadings obtained from the analysis using the CB-SEM method. Based on the findings, the indicators for each construct in the measurement model are the same as those in PLS-SEM. However, almost all of the loadings obtained through CB-SEM are lower than those from PLS-SEM, even though the researcher used the same scale during the unidimensionality procedure. Thus, PLS-SEM demonstrates that this method maximizes the explained variance of endogenous latent constructs (dependent variables) and minimizes the unexplained variance.

Table 4 Convergent Validity and Construct Reliability (CB-SEM)

Variables	Average Variance Extracted (AVE)	Composite Reliability	Cronbach's alpha
Nyata	0.575	0.844	0.844
Kebolehpercayaan	0.645	0.879	0.879
Tindakbalas	0.545	0.826	0.815
Empati	0.568	0.840	0.840
Kesetiaan Pelanggan	0.558	0.883	0.880

Comparative Analysis

Table 5 Comparison between PLS-SEM and CB-SEM

Variables	Average Variance Extracted (AVE)		Composite Reliability		Cronbach's alpha	
	PLS-SEM	CB-SEM	PLS-SEM	CB-SEM	PLS-SEM	CB-SEM
Nyata	0.680	0.575	0.894	0.844	0.860	0.844
Kebolehpercayaan	0.684	0.645	0.915	0.879	0.911	0.879
Tindakbalas	0.656	0.545	0.897	0.826	0.872	0.815
Empati	0.674	0.568	0.892	0.840	0.847	0.840
Kesetiaan Pelanggan	0.623	0.558	0.908	0.883	0.901	0.880

For convergent validity and composite reliability, the AVE values for the constructs of reliability, responsiveness, empathy, and customer loyalty are greater than 0.50, meeting the criteria set by Fornell and Larcker (1981). However, when compared to the AVE values obtained from the PLS-SEM method, all AVE values from CB-SEM are lower. Similar results are observed with composite reliability and Cronbach's alpha, where all values exceed the requirements set by Nunally (1978, 1994), but the values obtained through CB-SEM are lower compared to PLS-SEM.

PLS-SEM shows higher results, possibly due to its ability to handle models with many variables and complex relationships without requiring normal distribution assumptions. This makes it more flexible and suitable for studies involving data that do not meet the strict requirements of CB-SEM. Conversely, CB-SEM, while strong in testing theory and more specific models, requires stricter data conditions and may be less sensitive to small variations in the data. PLS-SEM offers flexibility and the capability to handle non-normal data and complex models but may be less precise in measuring causal relationships compared to CB-SEM. On the other hand, CB-SEM has strengths in theory testing and established models but requires more perfect data and stringent conditions. Understanding the strengths and limitations of each method can assist in choosing the appropriate method for future studies, based on specific needs and the nature of the available data.

Practical implications of this study are significant for both industry and academia. In the telecommunications industry, service providers can leverage PLS-SEM to design targeted strategies for improving customer loyalty by identifying the key drivers of satisfaction and trust. For instance, PLS-SEM's capability to handle complex constructs allows service providers to analyze the interplay between pricing, network quality, and customer service, thereby prioritizing investments in areas with the greatest impact. Additionally, regulatory bodies can use insights from CB-SEM analyses to benchmark service quality standards and promote fair competition, ensuring better customer outcomes. In academia, the findings provide a methodological framework for conducting comparative SEM analyses, which can be extended to industries such as healthcare, retail, and education. By exploring the strengths of PLS-SEM and CB-SEM, researchers can refine models for studying consumer behavior in diverse and dynamic environments.

This study's findings align with prior research highlighting the strengths of PLS-SEM in handling complex models and smaller sample sizes. For example, studies by Hair et al. (2017) and Suwanamas et al. (2016) demonstrated that PLS-SEM often produces higher AVE and CR values, consistent with our results. Similarly, our CB-SEM findings corroborate Zhang et al. (2020), who observed its sensitivity to strict data assumptions and its superior performance in confirmatory analyses when robust datasets are available. These consistencies underscore the reliability of our methodology and affirm the applicability of these SEM techniques across different contexts.

CONCLUSIONS AND RECOMMENDATIONS

The analysis results indicate that PLS-SEM tends to provide higher item loadings compared to CB-SEM. This suggests that PLS-SEM may be more sensitive in detecting relationships between constructs and measurement items. Additionally, the Average Variance Extracted (AVE) and Composite Reliability (CR) values obtained through PLS-SEM are also higher than those from CB-SEM. These findings have important implications for researchers and the industry. PLS-SEM, with its higher item loadings and better AVE and CR values, appears to be more suitable for models with high complexity and small sample sizes. This can aid researchers in selecting a more appropriate method for their studies, especially in scenarios where data is limited or the model structure is complex.

The comparison between the two methods shows that PLS-SEM typically provides higher composite reliability and convergent validity and explains more variance in dependent variable indicators (Hair et al., 2017). In direct comparisons, PLS-SEM retains more indicators, achieves higher composite reliability and convergent validity, and explains more variance in dependent variables compared to CB-SEM (Hair et al., 2017). However, some researchers have found that results from both approaches can be very similar (Amaro et al., 2015). The choice between PLS-SEM and CB-SEM depends on various factors including the research question, data characteristics, and available resources (Ahmed et al., 2024).

If the study involves a complex model with many variables and does not meet normal distribution assumptions, PLS-SEM is a more suitable choice. This is because PLS-SEM can handle complex model structures and data that do not adhere to strict requirements. Conversely, if the study aims to test established theories or models with data that meets stringent conditions, CB-SEM may be more appropriate. CB-SEM provides a deeper understanding of causal relationships and can more accurately test model validity. Researchers should consider the strengths and limitations of both methods when selecting the appropriate approach. PLS-SEM can be considered more flexible but may be less precise in measuring causal relationships. CB-SEM, although more accurate in theory contexts, requires more complete data and stringent conditions.

This study highlights the strengths of PLS-SEM in achieving higher construct validity and reliability compared to CB-SEM. Specifically, PLS-SEM demonstrated superior AVE and CR values, making it a more suitable choice for models involving smaller datasets, complex constructs, or non-normal data. CB-SEM, while effective for confirmatory analyses and theory testing, requires stricter data conditions and may underperform in exploratory scenarios. It underscores the importance of aligning SEM method selection with research objectives and data conditions. Key recommendations include:

i. Use PLS-SEM for exploratory research, especially when data are non-normal, sample sizes are small, or models are highly complex. Its flexibility makes it a practical choice for early-stage theory development and studies where predictive accuracy is critical.
ii. Apply CB-SEM for confirmatory analyses, particularly in studies with well-structured datasets and stringent theoretical frameworks. This method excels in testing established hypotheses and providing detailed insights into causal relationships.
iii. Explore hybrid SEM approaches, such as combining PLS-SEM and CB-SEM, to capitalize on their respective strengths. For example, hybrid methods could be used to refine exploratory models developed with PLS-SEM and validate them through CB-SEM.

Future research should extend this comparison to other industries, such as healthcare, retail, and education, where customer satisfaction and loyalty play pivotal roles. Additionally, industry-specific challenges, such as regulatory constraints or varying consumer expectations, could provide further insights into the applicability of SEM methods. Additionally, emerging SEM techniques like Bayesian SEM and hybrid PLS-CB SEM models should be explored to address evolving analytical challenges and enhance methodological robustness.

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