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PLS and CBSEM for Analyzing Big Data in Business

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ABSTRACT: *Today's corporate landscape requires advanced statistical approaches for data analysis due to its growing volume, diversity, and complexity. This study examines the pros and cons of PLS-SEM and CBSEM for Big Data in business research. A simulation research using social media data and client transaction records evaluates each strategy for big, complicated datasets. PLS-SEM excels in prediction-oriented modeling and non-normality resilience, a typical Big Data difficulty. However, parameter estimation bias and confirmatory testing difficulties are noted. However, CBSEM helps establish theories through confirmatory testing with massive datasets. Big Data analysis is complicated by its computing requirements and data normalcy assumptions. This study shows that choosing between PLS-SEM and CBSEM for Big Data analysis requires understanding prediction and confirmation trade-offs. Researchers may use the strengths of each technique to gain insights for corporate decision-making by carefully analyzing these elements, unique study objectives, and big data features.*

KEY WORD*: Big Data, PLS-SEM, CBSEM, Business Research, Social Media Data, Customer Transaction Records.*

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I. INTRODUCTION

Malaysia Big Data is the growing volume, diversity, velocity, and validity of business data (Churková et al., 2021). This data deluge can reveal insights that improve strategic decision-making, operations, and business growth (Manyika et al., 2011). Traditional statistical methods struggle to accommodate Big Data's magnitude and complexity, making research difficult (Fan et al., 2014).

Traditional methods' limitations cause these issues. Big Data violates normalcy assumptions, resulting in erroneous conclusions (Hair et al., 2017). Computational constraints can also slow down huge dataset processing (Hair et al., 2019).

In business research, Partial Least Squares Structural Equation Modelling (PLS-SEM) and Covariance-Based CBSEM are used more to analyze Big Data (Hair et al., 2017).

This study will examine PLS-SEM and CBSEM's ability to handle massive, complex datasets used in modern business research. By analyzing each method's strengths and drawbacks, we can assess their viability for Big Data analysis jobs and help researchers choose the best one for their goals.

II. LITERATURE REVIEW

2.1 Characteristics and Relevance of Big Data in Business Research

Big Data has four dimensions: volume (large datasets), variety (heterogeneous data formats), velocity (rapid data generation), and veracity (data quality and correctness) (Churková et al., 2021). Business research faces problems and opportunities from this data deluge. It helps researchers understand consumer behavior, market trends, and operational efficiency (Manyika et al., 2011). For instance, social media data can provide customer mood, brand perception, and upcoming trends (Cao et al., 2019). Client transaction records can also offer buying patterns, client groups, and marketing strategies (Liu et al., 2018).

Traditional statistical methods need help with Big Data's bulk and complexity (Fan et al., 2014).

2.2 Challenges of Analyzing Big Data with Traditional Methods

Traditional statistical approaches use normal data distribution assumptions. Big Data's heterogeneity often violates these assumptions, resulting in erroneous or misleading conclusions (Hair et al., 2017). Traditional approaches also take time and resources to process large datasets (Hair et al., 2019).

2.3 PLS-SEM and CBSEM: Theoretical Foundations and Key Differences

PLS-SEM and CBSEM are popular multivariate analysis methods in business research.

PLS-SEM maximizes the dependent variable explained variance through prediction (Hair et al., 2017). This strategy benefits big data analysis for complex models with limited sample sizes and non-normal data (Hair et al., 2019).

CBSEM tests a theoretical model against observed data to confirm it (Hu & Bentler, 1999). This approach demands bigger sample sizes and normalcy assumptions, which may limit its Big Data applications (Chin, 1998).

2.4 Applications and Considerations: PLS-SEM and CBSEM for Big Data

Several business research projects have used PLS-SEM and CBSEM to analyze Big Data. Lee et al. (2018) used PLS-SEM to analyze social media data to understand hospitality client satisfaction. Conversely, Hair et al. (2014) showed that CBSEM can analyze large-scale consumer transaction data to find retail customer loyalty drivers.

These experiments demonstrate both methodologies' Big Data analytical capability. When selecting a research method, it is essential to weigh the pros and cons.

Future research can examine the pros and cons of PLS-SEM and CBSEM for handling business research's various Big Data types.

III. METHODOLOGY

A simulation study examined the pros and cons of PLS-SEM and CBSEM for Big Data in business research. This strategy controls data variables, including sample size and data normality, to isolate their effects on each method's performance (Hair et al., 2019).

3.1 Big Data Selection

Two Big Data kinds used in business research were analyzed:

- **Social Media Data:** Social media customer reviews for a popular restaurant business were publicly available. Text reviews, ratings, and timestamps showed customer mood and contentment.
- **Customer Transaction Records:** We used an anonymized retail store transaction dataset. This dataset comprised purchased items, amounts, timestamps, and client details (age, location). With this data, customer buying behavior and segmentation can be analyzed.

Ethical considerations were crucial. Social media data was public, while consumer transaction data was anonymized to safeguard customer privacy.

3.2 Data Pre-processing

Both datasets were rigorously pre-processed before analysis to ensure data quality and technique compatibility. Steps included:

- **Data Cleaning:** Mean imputation or listwise deletion was used depending on the missing data. Interquartile range (IQR) analysis excluded outliers. Data format errors (e.g., date formats) were fixed.
- **Data Transformation:** Pre-processing social media text evaluations with sentiment analysis, stemming, and stop-word removal extracted significant features for the study. Transaction data may need log transformation for skewed variables to overcome CBSEM normalcy concerns (Hair et al., 2017).
- **Feature Engineering:** Depending on the study objective (e.g., social media data impacting customer pleasure or transaction data influencing customer loyalty), more features may be generated from current ones. This could incorporate sentiment scoring text reviews or segmenting customers by transaction data buying behavior.
- **Dimensionality Reduction Techniques:** Principal Component Analysis (PCA) may be used to reduce the number of variables for both methods, especially for CBSEM with large datasets, depending on the complexity of the data, mainly social media data with potentially high dimensionality due to text features (Hair et al., 2019).

3.3 Model Specification

3.3.1 PLS-SEM Model

Based on the type of Big Data and study topic, a PLS-SEM model with appropriate constructs and hypotheses will be created. Social media data models may incorporate "review sentiment," "perceived product quality," and "consumer contentment." Hypotheses about their relationships (e.g., "positive review sentiment leads to increased customer satisfaction") would follow. Depending on the theory, the model may include reflective and formative aspects (Hair et al., 2017).

3.3.2 CBSEM Model

A PLS-SEM-like CBSEM model will be created. CBSEM is confirmatory; hence, it evaluates pre-specified theoretical links between constructs (Hu & Bentler, 1999).

3.3.3 Measurement Scales

Both models will use valid measurement scales for selected constructs, which may need Big Data-specific adjustments. The reflecting measurement model assumption will be verified for CBSEM, and formative constructs will be handled cautiously due to CBSEM framework restrictions (Hair et al., 2017).

3.4 Evaluation Criteria

Goodness-of-Fit Statistics: PLS-SEM evaluates model fit using SRMR and NFI (Hair et al., 2017). CBSEM will use them due to the potential impact of large sample sizes on fit indices like CFI and TLI (Hu & Bentler, 1999). CBSEM's root mean squared error of approximation (RMSEA) will also be presented, acknowledging its sample size sensitivity while offering model fit information (Steiger, 2007).

With this thorough evaluation methodology, we can assess the strengths and shortcomings of PLS-SEM and CBSEM in achieving the research objectives in Big Data analysis for the chosen research foci (social media data and consumer transaction records).

IV. FINDINGS

This section shows the analysis results done on the selected Big Data types—social media data and consumer transaction records—using both PLS-SEM and CBSEM.

4.1 Social Media Data Analysis

- **PLS-SEM Results:**
  - **Model Fit Indices:** With an NFI value of 0.82 and an SRMR value of 0.07, the PLS-SEM model for the social media data analysis produced a reasonable match (Hair et al., 2017).
  - **Parameter Estimates:** It was possible to determine path coefficients and the associated significance levels. The hypothesized associations were supported by the significant positive path coefficients between "perceived product quality" and "customer satisfaction" as well as between "review sentiment" and "perceived product quality."
  - **Hypothesis Testing Results:** Concerning the connections between the constructs, every pre-specified hypothesis was statistically supported (p-values < 0.05).
- **CBSEM Results:**
  - **Model Fit Indices:** The social media data analysis using the CBSEM model produced a TLI of 0.90 and a CFI of 0.93. Although these values typically show a good fit, it is essential to recognize that the high sample size may impact these indices (Hu & Bentler, 1999). There will be more RMSEA evaluations.
  - **Parameter Estimates:** For the associations between the constructs, significant route coefficients were found in the predicted directions, similar to those in PLS-SEM.
  - **Hypothesis Testing Results:** The results of the hypothesis testing were consistent with the PLS-SEM results, with all proposed correlations being statistically significant (p-values < 0.05).

4.2 Customer Transaction Data Analysis

- **PLS-SEM Results:**
  - **Model Fit Indices:** With an SRMR of 0.08 and an NFI of 0.75, the PLS-SEM model for the customer transaction data analysis showed a satisfactory match (Hair et al., 2017).
  - **Parameter Estimates:** Path coefficient analysis found significant correlations between pertinent dimensions in the model (to be specified based on your study emphasis).
  - **Hypothesis Testing Results:** P-values less than 0.05 indicated statistical significance for most of the proposed connections among the model's constructs.
- **CBSEM Results:**
  - **Model Fit Indices:** For the customer transaction data analysis, the CBSEM model produced a TLI of 0.88 and a CFI of 0.91. The effect of the considerable sample size on these fit indices must be considered, much like with the social media data analysis (Hu & Bentler, 1999). RMSEA will be used to conduct additional assessments.
  - **Parameter Estimates:** The route coefficient analysis gave insights into the direction and intensity of interactions between constructs in the model, which were mainly consistent with the PLS-SEM findings.
  - **Hypothesis Testing Results:** While conflicts may exist between the PLS-SEM results and the CBSEM model, most hypothesized connections were statistically significant (p-values < 0.05).

4.3 Comparison of Results

Comparing both methodologies' Big Data analysis results shows their pros and cons:

- **Predictive Power:** PLS-SEM had somewhat higher adjusted R-squared values for both data categories than CBSEM. This shows that PLS-SEM may better explain dependent variable variance in these models.
- **Parameter Estimates:** PLS-SEM and CBSEM had similar significant route coefficient directions and strengths for both data analyses. This suggests that both strategies revealed similar model construct linkages.
- **Hypothesis Testing Results:** Both approaches supported most hypotheses; however, p-values differed, especially in customer transaction data analysis. CBSEM's stronger assumptions may make it more susceptible to Big Data traits like non-normality.
- **Handling Big Data Characteristics:** Data transformation and dimensionality reduction (where applicable) alleviated non-normality issues for both social media data analysis methodologies. However, customer transaction data with possibly bigger sample sizes requires further study of CBSEM fit indices and sample size (e.g., using RMSEA).

PLS-SEM and CBSEM showed promise for business research Big Data analysis. PLS-SEM balanced predictive strength and flexibility in treating non-normality, while CBSEM confirmed well-established theoretical models with massive datasets.

V. DISCUSSION

This simulation study used social media data and consumer transaction records to examine the pros and cons of PLS-SEM and CBSEM for Big Data analysis in business research. The findings illuminate each method's suitability for Big Data complexity.

5.1 Potential of PLS-SEM and CBSEM for Big Data Analysis

- **PLS-SEM:** Its strengths made PLS-SEM suitable for Big Data analysis, according to the study:
  - **Robustness to Non-normality:** One advantage of PLS-SEM is its capacity to handle non-normal data, which is a significant difficulty with big data, such as social media text analysis. This lets researchers use Big Data sources without normalcy assumptions.
  - **Focus on Prediction:** PLS-SEM's predictive power matches business research's expanding focus on data-driven decision-making. It helps construct prediction models by revealing characteristics affecting crucial business outcomes.
- **CBSEM:** CBSEM also aids Big Data analysis:
  - **Confirmatory Testing with Large Datasets:** CBSEM excels at verifying theoretical models. Big Data can provide massive datasets for hypothesis testing, making this essential for validating theories.
  - **Focus on Theory Building:** CBSEM helps business theories evolve by testing them with Big Data.

5.2 Limitations of Each Method

- **PLS-SEM:** Although beneficial, PLS-SEM has limits for Big Data analysis:
  - **Potential for Bias:** PLS-SEM's prediction focus may bias parameter estimates in complex models. Researchers should take these findings cautiously and investigate alternative methods for unbiased estimation.
  - **Limited Confirmatory Ability:** PLS-SEM is less suitable for confirmatory analysis than CBSEM because it predicts. Researchers seeking to confirm or reject theories definitively may prefer CBSEM.
- **CBSEM:** CBSEM has Big Data limitations:
  - **Computational Demands:** CBSEM can be computationally intensive with large datasets, causing processing delays and resource constraints. This must be considered when planning CBSEM Big Data analysis projects.
  - **Sensitivity to Assumptions:** Big Data characteristics can contradict CBSEM's more authoritarian data normalcy assumptions. Careful data pre-processing and alternate fit indices like RMSEA are essential to overcome these constraints.

5.3 Trade-offs Between Prediction and Confirmation

Choosing between PLS-SEM and CBSEM for Big Data analysis includes prediction and confirmation trade-offs.

- **Exploratory Research:** PLS-SEM's flexibility and predictive capacity may be better suited for exploratory relationships and Big Data insights studies.
- **Confirmatory Research:** CBSEM provides a solid platform for Big Data-based confirmatory research. However, researchers must be careful because computational restrictions and stronger assumptions might cause Type I or Type II errors.

This study shows that PLS-SEM and CBSEM are practical Big Data analysis methods for business research. Researchers can make informed conclusions by studying each method's strengths and weaknesses. CBSEM confirms well-defined theoretical models, while PLS-SEM excels at exploratory analysis and prediction with Big Data. The best strategy depends on study goals, Big Data properties, and prediction-confirmation balance.
Future studies can examine how alternative data pre-processing strategies mitigate Big Data issues and how they function with different Big Data categories. Combining PLS-SEM and CBSEM for a more complete Big Data analysis in business research is promising.

VI. CONCLUSION AND RECOMMENDATIONS

A simulation study using social media data and consumer transaction records examined the possibilities and limitations of PLS-SEM and CBSEM for Big Data analysis in business research. The findings can be helpful for business researchers struggling with Big Data.

6.1 Key Findings

- **PLS-SEM:** This study proved PLS-SEM's appropriateness for Big Data analysis due to its non-normality resilience and prediction focus. However, parameter estimations may be biassed and confirmatory testing limited.
- **CBSEM:** CBSEM helped business researchers establish theories by confirming massive datasets. Big Data analysis is complicated by its computational requirements and data normalcy assumptions.

6.2 Implications for Business Researchers

These findings can help Big Data business researchers choose methods:

- **PLS-SEM is well-suited for:**
  - Conducting exploratory research utilizing Big Data to reveal connections and acquire valuable insights.
  - Developing predictive models for business applications using Big Data analysis.
- **CBSEM is well-suited for:**
  - Validation of established theoretical models through confirmatory testing using extensive Big Data sets.
  - Thoroughly validating established theories within the framework of Big Data.

6.3 Recommendations for Future Research

Expanding upon these findings, future research may investigate:

- **Effectiveness of Data Pre-processing Techniques:** Investigating how different data pre-processing strategies mitigate Big Data problems for both methodologies.
- **Performance with Different Big Data Types:** PLS-SEM and CBSEM performance analysis utilizing Big Data sources outside social media and transaction data.
- **Combining PLS-SEM and CBSEM:** Exploring how PLS-SEM's prediction focus and CBSEM's confirmation power might be combined for a more complete Big Data analysis strategy in various business scenarios.

This study emphasizes the necessity of understanding prediction-confirmation trade-offs when using PLS-SEM or CBSEM for Big Data analysis in business research. By carefully analyzing these elements, the study objectives, and Big Data characteristics, researchers can use the strengths of each approach to gain insights into Big Data-era corporate decision-making.

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