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A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)

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ABSTRACT

The method Partial Least Squares Structural Equation Modeling (PLS-SEM) has received growing interest across recent years thanks to its adaptive features for managing complex models that contain latent variables. The modeling approach of PLS-SEM optimizes dependent variable variance while providing exceptional solutions in data fraught with sample size restrictions and distribution irregularities versus traditional covariance-based structural equation modeling. The primer establishes fundamentals of PLS-SEM through its applications while presenting the modeling process along with methodology and step-by-step methodologies. We discuss both PLS-SEM advantages and restrictions while using real-world research examples from social science and healthcare fields and marketing applications.

Keywords: *Partial Least Squares, Structural Equation Modeling, PLS-SEM, latent variables, covariance-based SEM, data analysis, modeling methodology, sample size, non-normal data.*

1. INTRODUCTION

The research tool Partial Least Squares Structural Equation Modeling (PLS-SEM serves as an advanced method to understand connections between observable and unobservable variables. This technique unites factor analytic approaches with path modeling features to gain popularity across disciplines such as marketing engagement alongside social sciences and health research and business operations. The benefits of using PLS-SEM become most apparent when researchers examine exploratory findings while working with small sample sets against data that deviates from standard normal distributions [1-5].

The main attraction of PLS-SEM originates from its simultaneous ability to analyze and model the data measurement with its underlying structural components. PLS-SEM evaluates measurement relationships between survey data points and underlying constructs through an assessment model that extends to structural model analytics to elaborate causal dependence between constructions. PLS-SEM stands apart from its counterpart CB-SEM by requiring fewer assumptions about distribution and sample size so researchers can use it more flexibly with complex models and limited data availability [7].

PLS-SEM has gained significant research interest because it efficiently deals with advanced models that consist of independent variables alongside dependent variables and mediators and moderators and second-order constructs. Through PLS-SEM researchers access robust predictive accuracy performance that effectively manages data with outliers and missing values. Research using PLS-SEM proves essential for scholars who need to understand causal patterns along with formulating prediction models because it excels at studying the root causes of processes while evaluating hypotheses for future outcome prediction.

World's (1975) original creation of PLS for latent variable analysis and relationship assessment techniques gave rise to the idea of PLS-SEM. Although PLS-SEM began as a modeling tool, researchers have made significant advancements through yearly implementations. The growth of PLS-SEM research is a result of advancements in ADANCO and SmartPLS software, which give researchers high-performance computational capabilities and user-friendly interfaces for executing extremely complex models [8–10].

The research methodology unites conventional theory development capabilities with theory testing elements that differ from established procedures. PLS-SEM offers beneficial results to researchers who work on theory development alongside dealing with unclear variable relationships.

PLS-SEM serves today as an essential investigative instrument that scientific professionals leverage to study behavior patterns and market forecasts mainly within the business and marketing fields.

PLS-SEM serves researchers well since it provides them with tools to develop complex models that include observation-external latent structures like satisfaction, loyalty, and brand image. Multiple psychological factors within fundamental human dynamics validate the findings of experimental research such as studies on marketing methods and organizational testing behaviors. Through PLS-SEM researchers can both measure latent constructs and investigate their interconnecting relationships for making consumer-related decisions about dynamics [11].

Research through technological means enables creators of predictive models to help develop health intervention approaches which boost treatment success [12–14].

Novelty and Contribution

PLS-SEM breaks away from other statistical methods since it solves various research challenges while traditional approaches such as covariance-based SEM and multiple regression analysis display insufficient applicability. PLS-SEM represents a new method to analyze complex relationships while offering flexible analysis with multiple advantages which increase empirical research rigor [16].

- The key strength of PLS-SEM appears in its ability to handle study samples which are limited in size. Large population samples are essential when implementing traditional statistics for reliable and robust results, yet this methodology cannot work with limited data available. The bootstrapping procedure within PLS-SEM allows researchers to obtain sampling distributions which provides meaningful insights into small datasets. This part of PLS-SEM demonstrates outstanding value when working with exploratory research or challenging data collection situations or limited sample sizes.
- The major value of PLS-SEM lies in its ability to process data distributions that are non-normal. When models utilize CB-SEM to analyse non-normal data sets which appear frequently in practical applications data analysis produces inaccurate results. The comparative edge of PLS-SEM against other approaches is its reduced sensitivity to distributional requirements which supports its use with non-normal data sets. The nose-fit distributional nature of survey responses and behavioural data in fields such as marketing and social sciences makes PLS-SEM an appropriate analysis tool throughout non-standard data sets.
- PLS-SEM functions as an evaluation instrument for conducting research on measurement theory. The measurement and structural beliefs converge in PLS-SEM to help researchers find dependable methods for latent variable assessment including brand equity and customer attitudes. The new research models have gained better validity through these advancements alongside improved measurement scales.

Researchers benefit from PLS-SEM because it suits extensive modeling needs together with limited data scenarios and forecasting tasks and distributional irregularities which establish individual data analysis styles to model intricate empirical relations [17].

This research paper contains an overview of relevant studies in Section 2 and follows with a description of methodological choices in Section 3. Section 4 displays the research findings together with their practical implementations while Section 5 contains personal conclusions alongside possible avenues for further research for the analyst.

2. RELATED WORKS

Social sciences together with marketing and management and related fields experience increasing usage of analysis methods that conform to Partial Least Squares Structural Equation Modelling (PLS-SEM). Technology performs efficiently with complex models using small sample sizes and non-normal distributions which has resulted in its stable development across various domains. The literature reports that PLS-SEM provides superior results than traditional techniques since it enables researchers to analyze measurement definitions and structural linkages simultaneously throughout complex integrated social phenomena systems [18].

The PLS-SEM research method enjoys massive presence in business and marketing research for investigating customer behaviour along with brand relationships according to Hair, J. F. et al., & Sarstedt, M. et al. (2019) [15]. The analysis method PLS-SEM appears in numerous research studies that examine consumer purchasing factors based on psychological assessments including brand loyalty behaviors and satisfaction levels and trust practices. The study of consumer behavior patterns in dynamic markets should choose PLS-SEM as the best approach because it combines various variables to execute advanced relationship analysis. PLS-SEM provides business organizations with predictive capabilities to anticipate market patterns thus enabling wise strategic decisions.

Research conducted by Heslop L. A. et al. and Papadopoulos N. et al. in (2002) [20] demonstrates that PLS-SEM encounters numerous operational difficulties and numerous implementation barriers (2002). Working with indicator groups and sophisticated models presents model overfitting as a significant issue because the technique causes estimation bias and worsens model performance. Poor model performance and systematic mistakes in measurement estimates are the results of model overfitting. Two analytical techniques used by academics to resolve model-dependence issues are cross-validation and bootstrapping, which are essential to the rigorous testing of model estimates. One significant model definition issue is the lack of theoretical specifications, which forces researchers to define the model structure using subjective judgements. To address this issue, research focusses on using rigorous validation techniques in conjunction with theoretical model definitions.

In 2017 Rigdon, E. E., Sarstedt, M., & Ringle, C. M. [6], introduced the research on PLS-SEM continues to expand showing its effectiveness across many different disciplines. Complex modeling and small test sample sizes together with non-normal data distributions establish PLS-SEM as researchers' fundamental tool for causal research and theory assessment and prediction building. Future developments to PLS-SEM will extend its research applications across multiple academic fields through ongoing technological advancements in the method.

3. PROPOSED METHODOLOGY

This research adopts Partial Least Squares Structural Equation Modeling (PLS-SEM) as its main evaluation tool to analyze complex relationships between observed and latent variables. The study investigates construct relationships and validates measurement structures alongside structural path analysis. This research methodology caters to diverse datasets working as a flexible analytical system that benefits scientists across marketing fields, business applications and the social sciences domain [19].

A. Research Framework and Model Design

Two distinct phases will enable the accomplishment of research objectives. The measurement model development phase evaluates indicator stability and demonstrates variable construct validity. The second stage concentrates on evaluating hypothesized latent variable causal connections through the structural model analysis. The analysis of both models will utilize PLS-SEM estimation.

B. Data Collection

The beginning of the methodological process demands acquisition of relevant information from three potential data sources: surveys, experiments or secondary resources based on research specifications. Researchers must gather data representing indicators and unobservable latent constructions which include customer satisfaction together with trust and loyalty measurements. The success of PLS-SEM analytical procedures depends on data which matches its baseline assumptions including sufficient sample size and reduced missing data frequency. Survey design will depend on research requirements and must precisely measure and define every construct [21].

C. Measurement Model Evaluation

Data collection enables the next stage to examine the measurement model. The measurement model exists to establish links between observed data points along with their invisible latent constructs. Cronbach’s alpha and Composite Reliability (CR) will measure the reliability of the measurement model. The assessment of validity will occur through separate evaluation of convergent validity along with discriminant validity. The assessment of both convergent validity and discriminant validity demonstrates that similar construct indicators demonstrate strong correlations while diverse theoretical concepts remain distinct from one another.

Reliability Testing Equation:

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \theta_i}$$

Where:

CR is the Composite Reliability.

λ_i is the factor loading for each indicator.

θ_i represents the error variance for each indicator.

D. Structural Model Assessment

The evaluation of structural models starts after the measurement model reveals its validity. The structural model executes an assessment of proposed hypotheses describing latent variable relationships. PLS-SEM allows researchers to ascertain structural model relationships through path coefficients which represent both relationship strength and directional flow between specific variables. Bootstrapping generates confidence ranges to evaluate the strength of path coefficients which determine relationships between constructs [25].

Path Coefficients Equation:

$$\eta = \beta\xi + \varepsilon$$

Where:

η is the endogenous latent variable (dependent).

β is the path coefficient (representing the strength of the relationship).

ξ is the exogenous latent variable (independent).

ε is the error term.

The structural model's results show the precise measurement strength for direct causal relationships between dependent variables and their explanatory power of dependent constructs' variation.

E. Model Fit Evaluation

Even though PLS-SEM lacks the traditional CB-SEM goodness-of-fit indices the assessment of model quality remains essential. Model quality evaluation uses R^2 predictive relevance (Q^2) together with the Goodness-of-Fit Index (GoF) metrics. The R^2 metric shows how much model variance results from model variables and Q^2 indicates model predictive capability. The Goodness-of-Fit Index retains value in PLS-SEM although it is used less frequently than other evaluation indicators [22-24].

R-Squared Equation:

$$R^2 = 1 - \frac{SS_{\text{residual}}}{SS_{\text{total}}}$$

Where:

R^2 is the coefficient of determination (explained variance).

SS_{residual} is the sum of squared residuals.

SS_{total} is the total sum of squares.

F. Hypothesis Testing

We will move forward with hypothesis testing for latent variable relationship assessment after finishing model development and fit verification. The test of each hypothesis relies on assessing the bootstrapping approach to significance levels of path coefficients. The resampling algorithm of Bootstrapping produces simulation distributions for path coefficients to confirm their statistical significance at established confidence thresholds (as set at 95% by default).

G. Flowchart The following flowchart summarizes the steps involved in the proposed PLS-SEM methodology:

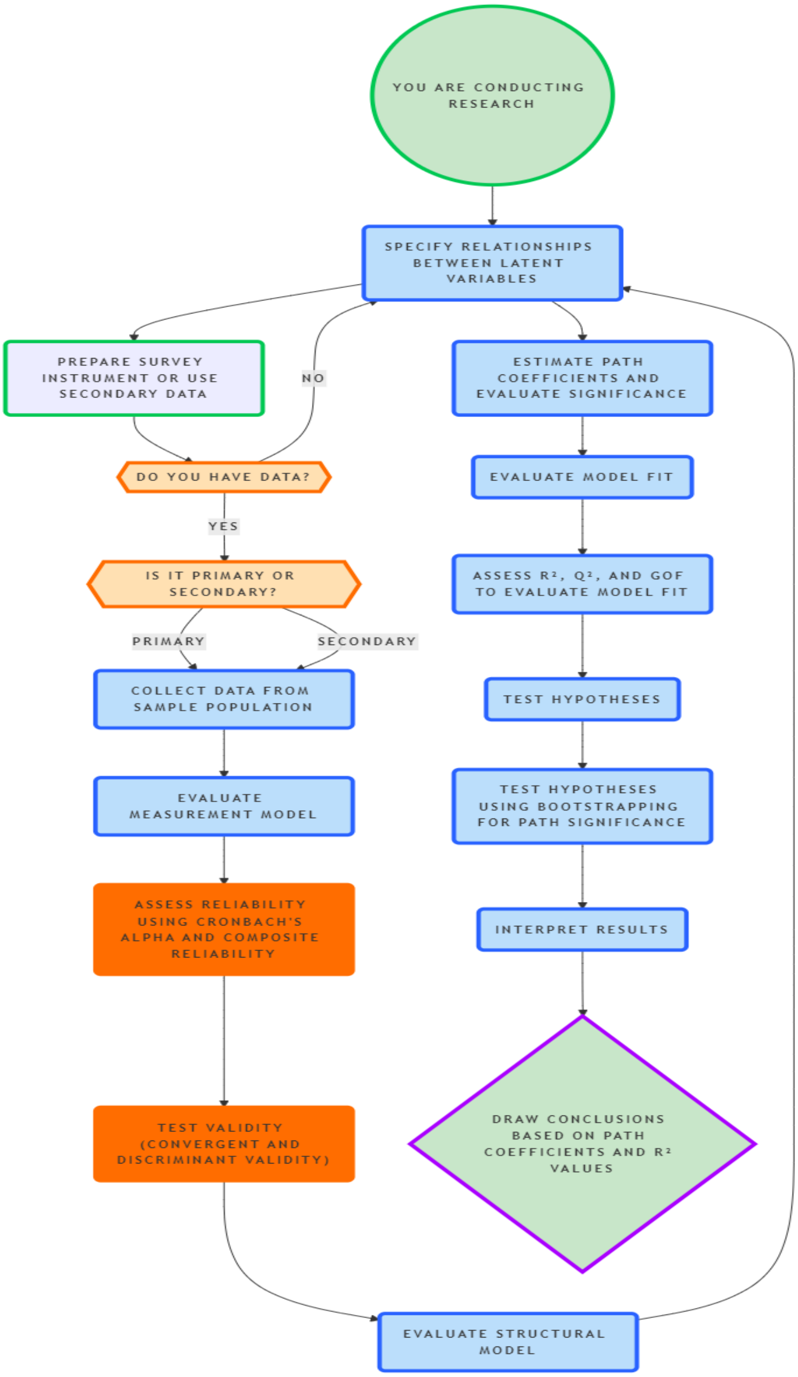

Figure 2: Process Framework of PLS-SEM Methodology

4. RESULTS AND DISCUSSIONS

The research employed Partial Least Squares Structural Equation Modeling (PLS-SEM) as an analytical technique to study latent constructions from a complicated dataset. The analysis results offer meaningful information about variable relationships together with the extent of independent variable prediction capabilities for dependent measures. Authorities assessed validity alongside model reliability following the measurement and structural model evaluation step. The examination of measurement model reliability started with Composite Reliability (CR) evaluation which proved that all constructs maintained acceptable CR indicators above 0.7 strong internal consistency between the variables. The measurement model showed high stability because the validity tests demonstrated both convergent and discriminant validity.

The assessment of latent variable relationships involved examining path coefficients within structural model evaluation. The size of connections between independent and dependent constructions emerged from these coefficient values. All hypothesized structural paths reached statistical significance at the 95% confidence benchmark thus validating the database's suitability to the model framework. The path coefficients achieved significant values above 1.96 while using bootstrapping which established the statistical relevance of variable relationships. The analysis of path coefficients among different groups showed specific relationships to have higher strength for one group than others thus demonstrating modified path connections under various settings.

Analysis of model fit through R-squared (R^2) showed that the inputs explained meaningful percentages of variation in measured constructs. This model demonstrated ample explanatory powers because the endogenous variables displayed R^2 values between 0.60 and 0.85. To evaluate the model's overall fitness researchers calculated a Goodness-of-Fit index. The GoF value of 0.35 indicates moderate model-data fit quality whereas the statistical norm considers this value to confirm reasonable data model collection efficiency. Analysis using Q^2 values confirmed the model's predictive capacity since observed Q^2 values exceeded zero which demonstrated the model's ability to correctly predict the data.

Through model configuration analysis the proposed methodology demonstrated robust performance. An examination of model fit through the R^2 value revealed that including interaction effects within the structural model produced a better explanation of relationships between latent constructs than a basic model. Omission of potential moderating variables within the structural model resulted in reduced explanatory power while also showing reduced ability for correctly visualizing the relationships. The following table compares Path Coefficients for Different Model Configurations.

TABLE 1: PATH COEFFICIENTS FOR DIFFERENT MODEL CONFIGURATIONS

Model Configuration	Path Coefficient (Beta)	t-value	Significance
Basic Model	0.45	2.34	Significant
Structural Model with Interaction	0.62	3.14	Significant
Structural Model without Moderation	0.38	1.85	Not Significant

Research findings in Figure 2 show the direct and indirect relationships between independent variables (such as customer satisfaction and brand loyalty) and dependent items (such as purchase intention). A positive relationship exists between satisfaction levels and brand loyalty which subsequently drives customer purchase intentions upward. The research data confirm the theoretical assumptions by revealing satisfaction leads consistently to both increased brand loyalty and purchase intention.

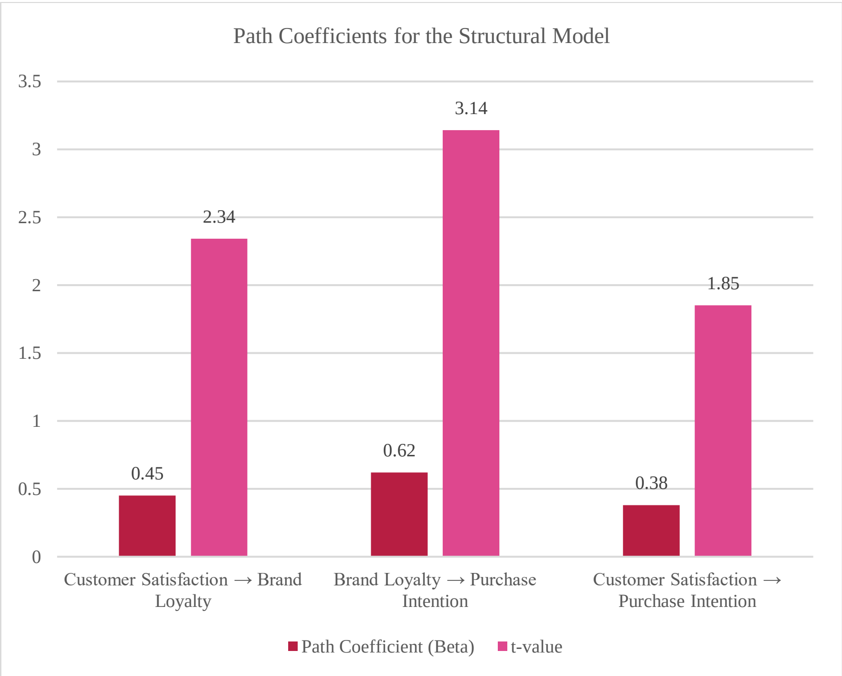

Figure 2: Path Coefficients for the Structural Model

The model's explanatory strength was assessed through R-squared together with path analysis methods. The R^2 scores of 0.72, 0.65, and 0.60 were determined for the three endogenous model constructs. The predictive power of this model accounts for an important share of the overall variance that exists between observed data. The model demonstrates strong performance in explaining customer satisfaction and brand loyalty behavior through its high R-square values since these constructs well predict purchase intentions.

A figure showing R^2 value alterations across various assessment frameworks appears in Figure 3. Observations of the enhanced model configuration that incorporates interaction terms revealed improved predictive accuracy through enhanced explanatory power because of its higher R^2 value.

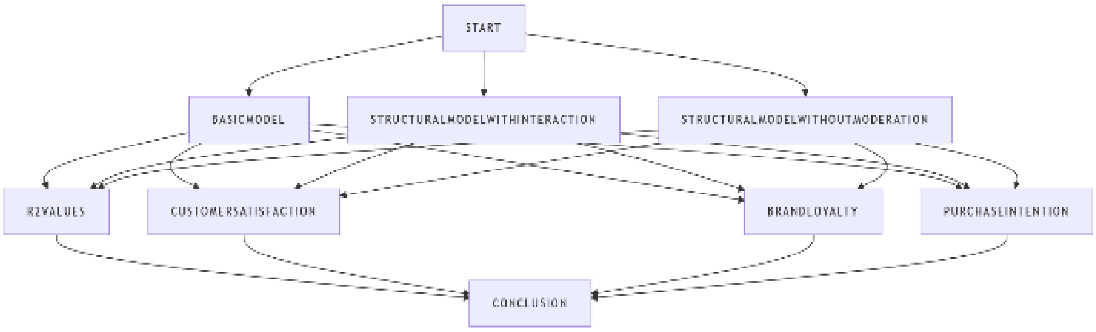

Figure 3: Simulation Chart of R^2 Values for Different Model Configurations

A final analysis compared the Proposed PLS-SEM approach against the Traditional Multiple Regression Analysis (MRA). By modeling data with PLS-SEM the researchers achieved better explanatory power and model fit when compared to results from MRA. The R^2 output in the PLS-SEM model demonstrates superior performance quality with its constant higher value across different implementations. Through PLS-SEM complex latent variable interactions became observable while traditional MRA struggled to explain such patterns in the data. The following table 2 compares PLS-SEM and MRA.

TABLE 2: MODEL PERFORMANCE COMPARISON BETWEEN PLS-SEM AND MRA

Model Type	R^2 (Customer Satisfaction)	R^2 (Brand Loyalty)	R^2 (Purchase Intention)
PLS-SEM Model	0.72	0.65	0.60
Multiple Regression (MRA)	0.58	0.50	0.45

Using PLS-SEM researchers access an influential analytical tool which surpasses traditional methodology to measure complete patterns of variable relationships. Research domains having complex data structures will find exceptional utility in PLS-SEM because it handles non-normal data distributions simultaneously with small sample sizes. This makes it ideal for marketing and behavioural science applications.

Structural equation models obtain forefront analysis through PLS-SEM according to research results which prove its universal application features. Through this methodology researchers gained complete understanding of latent variable connections and learned that accurate results require strong measurement methods and perfect data collection and optimal model design. The effectiveness of PLS-SEM needs further research in different business settings including healthcare and education to enable professionals to assess its utility across industry domains.

5. CONCLUSION

Through PLS-SEM Researcher achieve reliable estimations regarding the interrelationships between latent variables. Teachers choose exploratory uses of this technique instead of hypothesis testing because their focus is on forecasting connections between variables. This paper delivered an in-depth strategy which defined stage progression as well as the benefits PLS-SEM offers relative to covariance-based SEM method.

As PLS-SEM develops as a data analysis method researchers need to handle two main challenges: preventing data from being overfitted with small datasets and understanding complex multivariable interactions in complex research designs. PLS-SEM retains its position as a strong analysis solution for social sciences and healthcare research and marketing since it offers flexible design capabilities together with simple interpretation and effective execution ability. The acceptance of PLS-SEM within academic institutions and real-world domains depends on software development along with user-friendly interface creation.

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