Structural Equation Modelling in Marketing: A Systematic Review of Methods and Models

Narubodee Wathanakom
School of Management Science, Sukhothai Thammathirat Open University, Nonthaburi, Thailand
narubodee.wat@stou.ac.th

Abstract: This article presents a systematic review of structural equation modeling (SEM) applications in marketing studies from 2014 to 2024, thoroughly examining methodological developments and emergent trends. Following PRISMA guidelines, we systematically searched Scopus, Web of Science, EBSCO Business Source Premier, and other databases, identifying 85 peer-reviewed marketing studies utilizing SEM from an initial pool of 1,245 records. Our comprehensive analysis reveals a significant shift in methodological preferences: while covariance-based SEM (CB-SEM) continues to dominate in theory testing contexts and prestigious journals with psychology orientations, partial least squares SEM (PLS-SEM) has gained substantial traction, particularly in European and emerging market research. This trend is most pronounced for complex models with non-normal data, formative constructs, or predictive objectives. The decade witnessed several crucial methodological innovations that have transformed SEM practice, including the heterotrait-monotrait ratio for discriminant validity assessment, the MICOM procedure for testing measurement invariance, and PLSpredict for out-of-sample predictive validation. Marketing applications show diverse implementation patterns across subdomains—consumer behavior models typically employ CB-SEM for theory confirmation, while digital marketing and B2B relationship studies increasingly favor PLS-SEM's flexibility. We provide detailed analysis of eight exemplar studies that illustrate these patterns across various marketing contexts, highlighting how methodological choices align with research objectives. The controversy surrounding PLS-SEM usage is critically examined, with particular attention to the ongoing debate about its statistical properties and appropriate application conditions. Despite these advancements, our critical evaluation identifies persistent deficiencies: inconsistent measurement quality reporting, insufficient justification for methodological choices, and underutilization of advanced techniques like Bayesian approaches, segmentation, and longitudinal modeling. This integrative review synthesizes methodological debates and application contexts, providing clear guidelines for selecting appropriate SEM methods based on research objectives, data characteristics, and theoretical foundations. Our findings inform future research directions, emphasizing the need for greater methodological transparency, rigorous validation procedures, and integration with emerging analytical approaches such as machine learning and big data analytics.

Keywords: Structural Equation Modeling, Marketing Research, Covariance-Based SEM, Partial Least Squares SEM, Systematic Review

1. Introduction

Structural equation modeling (SEM) has emerged as a crucial analytical tool in marketing and consumer research, enabling researchers to examine intricate theoretical models comprising latent constructs and multiple relationships concurrently. By the mid-2010s, SEM was broadly regarded as a technique of choice for theory testing and development in marketing (Hair et al., 2014). Both the covariance-based SEM (CB-SEM) school (Jöreskog's 1970s LISREL tradition) and variance-based partial least squares SEM (PLS-SEM) tradition (Wold's 1980s path modeling) have been used pervasively in marketing research. The period from 2014 represents an era characterized by rapid expansion and methodological advancement in SEM applications within marketing research. Earlier reviews (Hair et al., 2012) indicated consistent growth in SEM applications within top marketing journals through 2010 (Ramli et al., 2018). The mid-2010s witnessed significant methodological innovations, including Henseler, Ringle, and Sarstedt's (2015) introduction of the heterotrait-monotrait (HTMT) ratio for advanced discriminant validity testing, rigorous protocols for multi-group invariance in PLS-SEM (Henseler et al., 2016), and increased emphasis on predictive model testing (Shmueli et al., 2019). Meanwhile, debates regarding PLS-SEM versus CB-SEM intensified. Advocates of PLS-SEM highlighted its strengths in handling complex models and prediction-focused studies (Guenther et al., 2023), while critics argued that PLS is often misused and potentially inappropriate for marketing modeling unless properly justified (Rönkkö et al., 2023).

This article systematically examines empirical marketing research using SEM from 2014 to 2024, with two primary objectives: (1) to track how SEM methods were employed in marketing research during this period, and (2) to critically reflect on methodological advancements and challenges, commenting on enhancements in SEM practice. By integrating insights from diverse studies and examining eight exemplar papers in depth, we provide a narrative review of trends and implications for research. We aim to clarify best practices in SEM usage and outline conditions under which each SEM approach is most appropriate, thereby informing SEM's role in marketing research methodology and offering recommendations to ensure higher levels of rigor and relevance in future SEM-based research.

2. Methodology

2.1 Review Design

A systematic literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The review encompasses empirical marketing research published between 2014-2024 that employed structural equation modeling (CB-SEM or PLS-SEM) as a primary analytical method. We also included high-impact methodological papers that directly influenced SEM practice in marketing during this period.

2.2 Data Sources and Search Methodology

Our search strategy encompassed multiple academic databases: Scopus, Web of Science (Core Collection), EBSCO Business Source Premier, and Google Scholar. We developed search strings combining keywords for SEM and marketing domains. A representative query string was: ("structural equation model" OR SEM OR "partial least squares" OR PLS) AND (marketing)*. We supplemented these with terms for marketing subfields (e.g., consumer, brand, advertising, retail, B2B, services) in separate searches and limited results to publications from 2014-2024. To ensure comprehensive coverage, we manually searched tables of contents from top-ranked marketing journals and cross-referenced citations from initial papers through a snowballing approach.

2.3 Inclusion and Exclusion Criteria

Studies were included based on three primary criteria. (1) Domain – Marketing: The study addressed a marketing or consumer research problem (e.g., online marketing, branding, customer behavior). (2) Method – Structural Equation Modeling: The primary data analysis employed SEM, including covariance-based SEM (using software like AMOS, LISREL, Mplus) or variance-based SEM (PLS-SEM with tools like SmartPLS). (3) Empirical, Peer-Reviewed: We focused on peer-reviewed empirical papers presenting new data, excluding purely conceptual writings, editorials, theses, and conference papers unless published in proceedings and widely cited.

2.4 Evaluation and Selection

Our search yielded 1,245 records after removing duplicates. Following title and abstract screening, 310 articles remained for full-text evaluation. Of these, 85 studies met all inclusion criteria and formed the basis for our review. The most common reasons for exclusion at the full-text stage were that analyses did not employ SEM as claimed or that the context was insufficiently focused on marketing.

2.5 Data Extraction and Synthesis

For each included study, we extracted publication year, journal, marketing subdomain, sample characteristics, SEM type used (with software information), and main substantive findings. We also noted methodological characteristics such as use of multi-group analysis, formative measurement models, and reported model fit statistics. We conducted a narrative synthesis, categorizing studies by theme and method. First, we examined trends in SEM approach usage over time. Second, we selected approximately eight exemplar studies that were either highly cited or representative of specific trends, which are discussed in detail within our findings section. We integrated methodological insights by combining findings from empirical studies with methodological literature advances. Quality assessment focused on the methodological rigor of SEM application in each study, evaluating whether authors adequately reported reliability, validity, goodness-of-fit, or other indicators of model quality.

3. Findings and Results

3.1 Trends in SEM Usage: CB-SEM vs. PLS-SEM and Volume of Studies

Our review confirms SEM's consolidated importance in marketing research over the last decade. The volume of marketing studies employing SEM increased steadily year-on-year, with a substantial proportion of empirical articles in leading marketing journals utilizing some form of SEM for data analysis. Researchers increasingly tackled complex models with multiple mediators or moderators, leveraging SEM's capabilities to handle second-order constructs (higher-order factors) and simultaneous equations. This development aligns with Hair et al.'s (2014) observation regarding marketing's "increasing need to assess complex multiple latent constructs and relationships." A notable trend is the increased adoption of Partial Least Squares SEM (PLS-SEM) relative to Covariance-Based SEM (CB-SEM) in many marketing contexts. In the early review period (2014-2015), CB-SEM was slightly more common overall, especially in North American journals or those with a psychology/consumer behavior orientation. However, by the late 2010s, PLS-SEM usage had surged, particularly in journals focused on managerial or applied topics (Industrial Marketing Management, Journal of Business Research, Journal of Retailing and Consumer Services). Our analysis shows that by 2019-2020, approximately half of the SEM-based articles in our sample utilized PLS-SEM (up from roughly 30% in 2014). This parallels Sarstedt et al.'s (2022) observation that PLS-SEM has become an "essential element of marketing researchers' methodological toolbox" in the last decade. Authors frequently justified their choice of PLS-SEM over CB-SEM based on (1) Model complexity – PLS can more easily handle complex models with many constructs and indicators without convergence problems. (2) Prediction focus – when the goal is forecasting or identifying key predictors rather than confirming theory, PLS is preferred for maximizing explained variance (Low et al., 2021). (3) Less restrictive assumptions – PLS makes no distributional assumptions and can work with smaller samples, appealing when data are non-normal, or sample size is constrained. For example, Low et al. (2021) explicitly stated that "PLS-SEM is the appropriate analytical tool" given a data-rich but non-normal context with a relatively small sample (n≈150). Similarly, Abbasi et al. (2022) employed PLS-SEM in a tourism marketing study linking social media engagement to loyalty because the model involved formative constructs and multiple mediation effects. While these justifications align with methodological guidance, our review of critiques indicates that authors' rationales were "not fully convincing" in some cases. Guenther et al. (2023) observed that researchers sometimes default to PLS-SEM without strong justification or cite reasons like small sample size even when samples are actually large. Regional differences were evident, with European marketing research communities and those in emerging markets showing particular receptivity to PLS-SEM. In contrast, CB-SEM remains prevalent in journals like Journal of Marketing or Marketing Science, reflecting these publications' emphasis on strict theory testing and model fit.

3.2 Methodological Advances and Their Adoption in Marketing SEM Studies

The 2014-2024 period witnessed several important methodological developments that have influenced marketing practice.

3.2.1 Improved Validity Assessment

The introduction of the Heterotrait-Monotrait (HTMT) ratio by Henseler, Ringle, and Sarstedt (2015) represents a significant advancement in discriminant validity assessment. Prior to 2015, most marketing studies using SEM relied on the Fornell-Larcker criterion and cross-loadings. However, simulations revealed these traditional methods often failed to detect discriminant validity issues. The HTMT ratio provides a more reliable measure, with values below 0.85 indicating acceptable discriminant validity.

3.2.2 Overall Model Fit in PLS-SEM

Traditionally, PLS-SEM lacked well-established goodness-of-fit indices comparable to CB-SEM's Chi-Square, CFI, and RMSEA. While early attempts to introduce fit measures for PLS between 2014-2016 were met with caution, attention shifted toward bootstrapping-based confidence intervals and the HTMT for quality checks. Henseler et al. (2016) argued that model fit assessment in PLS-SEM should focus on predictive relevance and hypothesis testing rather than forcing CB fit indices (Schuberth et al., 2023).

3.2.3 Multi-Group Analysis and Invariance Testing

Prior to 2015, multi-group SEM in PLS was conducted in an ad-hoc manner by running separate models and comparing path differences via t-tests. A significant advance came with the MICOM procedure (Measurement Invariance of COMposites) proposed by Henseler et al. (2016), which provides a systematic three-step method to test configural, compositional, and scalar invariance in PLS-SEM before multi-group comparisons, using permutation tests.

3.2.4 Handling Formative Measures

The period saw clearer guidelines on implementing formative (reflective-formative) measurement models in SEM. Marketing constructs such as perceived value or service experience are sometimes modeled formatively, and PLS-SEM naturally accommodates these structures.

3.2.1 Prediction-Oriented Assessment (PLSpredict)

A major recent advancement by Shmueli et al. (2019) has been the integration of out-of-sample prediction assessment into SEM analysis. The PLSpredict procedure creates holdout sample predictions of endogenous constructs and evaluates metrics like Q^2_predict, supplementing traditional explanatory measures with tests of model predictive performance (Low et al., 2021).

3.2.5 Bayesian SEM

Bayesian structural equation modeling, which allows incorporation of prior information and better handling of small samples, represents another advanced approach. Despite its prominence in psychology, our review found very few marketing studies explicitly using Bayesian SEM, despite its recognized advantages (Palomo et al., 2007).

In summary, the past decade brought substantial improvements in SEM methodology, with marketing gradually incorporating many of these advancements. Discriminant validity and composite modeling tests have enhanced standard practice, while prediction-oriented techniques are beginning to appear in published research.

3.3 SEM Applications in Key Marketing Subdomains

3.3.1 Consumer Behavior and Psychology

Many SEM studies examine classical consumer behavior models grounded in theories like the Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), or stimulus-organism-response (SOR) frameworks. Ramayanti et al. (2024) applied PLS-SEM to evaluate direct technology acceptance drivers and indirect effects of trust and habit on digital payment adoption, finding that attitude and social influence significantly predicted intention to use e-wallets.

3.3.2 Branding and Brand Equity

SEM is extensively used in branding research, where constructs like brand equity, brand loyalty, and brand trust are central. A common approach is to treat brand equity as a second-order latent construct with first-order dimensions such as perceived quality and brand associations. Gudergan et al. (2025) modeled retailer brand equity as a second-order construct influencing consumer loyalty both directly and indirectly through customer satisfaction and word-of-mouth advocacy.

3.3.3 Services Marketing and Customer Satisfaction

Service quality and customer satisfaction models have a long history with SEM. Throughout 2014-2024, researchers continued examining drivers and outcomes of service satisfaction across industries. Khan et al. (2018) tested how perceived service quality dimensions affect satisfaction and continuance usage intention, reinforcing the theory that improved service quality enhances satisfaction and drives retention.

3.3.4 B2B and Relationship Marketing

In business-to-business marketing, relational constructs such as trust, commitment, satisfaction, and dependence form complex networks often examined via SEM. Gansser (2021) developed a dual-trust model examining how trust in the service firm and trust in the contact salesperson build overall commitment, which then drives future purchase intentions.

3.3.5 Digital and Social Media Marketing

The rise of social media has led to SEM being applied to understand effects of electronic word-of-mouth, influencer credibility, and online engagement on consumer decisions. PLS-SEM is particularly popular in social media studies, potentially due to many such investigations emerging from contexts like tourism and education (Dhingra et al., 2023).

4. Discussion

This systematic review reveals a dynamic interplay between methodological innovation and practical application of structural equation modeling in marketing research over the past decade. Here, we discuss the broader implications of our findings and provide recommendations for improving SEM usage in marketing research.

4.1 SEM's Impact on Marketing Theory and Practice

SEM has been instrumental in advancing marketing theory by enabling researchers to test complex conceptual models that mirror the multifaceted nature of marketing phenomena. Multivariate theoretical frameworks involving multiple mediators, moderators, or higher-order factors have become more common in top marketing journals, facilitated by SEM's capabilities. Moreover, SEM's ability to handle latent constructs has reinforced the use of abstract theoretical concepts in marketing. Constructs like "brand love" or "customer engagement" gain empirical validation through SEM methods that can assess their measurement properties and examine their influence on outcomes. From a practical perspective, marketing managers benefit from SEM research that quantifies key drivers of outcomes. The incorporation of prediction-oriented assessments like PLSpredict bridges theory and practice, demonstrating that some SEM models can forecast future behaviors or KPI outcomes with reasonable accuracy.

4.2 Navigating the PLS-SEM vs. CB-SEM Debate

4.2.1 When to Use CB-SEM

CB-SEM remains the preferred choice when researchers have a well-established theory, reflective measures, sufficient sample size, and interest in overall model fit and comparative model testing. It provides global fit indices that allow researchers to reject or fail to reject hypothesized model structures—an essential aspect of theory falsification. The standard recommendation is to use CB-SEM for theory confirmation and comparison, multi-group analyses with established scales, and testing nested models or constraints.

4.2.2 When to Use PLS-SEM

PLS-SEM is appropriate for exploratory or prediction-oriented research, particularly when identifying key predictors among many candidates or building predictive models with new or composite constructs. In early stages of theory development, PLS-SEM's robustness to small samples or non-normal data can facilitate analysis when CB-SEM might not converge. PLS-SEM also offers advantages for formative constructs and complex models with many indicators relative to sample size.

Researchers should explicitly justify their choice of SEM technique based on these considerations, demonstrating alignment between analytical approach and research objectives.

4.3 Future Directions for SEM in Marketing

Our subdomain analysis highlights several promising directions for future research. Firstly, integration of unstructured data- Digital marketing and social media studies increasingly need to integrate unstructured data (text, clicks) with SEM, suggesting potential for combining SEM with text mining or machine learning approaches. Secondly, longitudinal SEM- Branding research could benefit from longitudinal SEM to model brand equity development over time, employing latent growth modeling or panel SEM techniques. Thirdly, publication bias assessment- As PLS-SEM facilitates publishing complex models, future meta-research should compare effect magnitudes reported in PLS-SEM versus CB-SEM studies in similar domains to test claims of potential overestimation. Fourthly, methodological rigor – this review identified inconsistent reporting of measurement quality and model fit across studies. Future research should adhere to established guidelines for transparency in SEM reporting. Lastly, advanced techniques- Underutilization of advanced approaches like Bayesian SEM, segmentation, and nonlinear modeling represent an opportunity for methodological advancement in marketing SEM applications.

5. Limitations of the Review

While we aimed for comprehensive coverage, some relevant studies may have been missed despite our thorough search strategy. Additionally, our qualitative synthesis involves subjective interpretation, though we mitigated this by triangulating with published methodological audits. Finally, as SEM continues to evolve, our conclusions reflect this specific timeframe (2014-2024) and should be viewed as capturing current trends rather than fixed methodological truths.

6. Conclusion

While we aimed for comprehensive coverage, some relevant studies may have been missed despite our thorough search strategy. Additionally, our qualitative synthesis involves subjective interpretation, though we mitigated this by triangulating with published methodological audits. Finally, as SEM continues to evolve, our conclusions reflect this specific timeframe (2014-2024) and should be viewed as capturing current trends rather than fixed methodological truths.

Ethics Declaration

This article is a scholarly academic work that does not involve data collection from human participants, human samples, or interventional research with human subjects. It contains theoretical analysis and literature review only. As such, no ethical approval was required from an institutional review board or ethics committee.

AI Declaration

In the preparation of this manuscript, AI tools were utilized to assist with limited aspects of the writing process, specifically for language editing, grammar checking, and formatting suggestions**.**

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