REIMAGINING CONSUMER ANALYTICS: PREDICTIVE AND REAL-TIME INSIGHTS THROUGH DYNAMIC STRUCTURAL EQUATION MODELING

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ABSTRACT

Background: Prior research had predominantly emphasized traditional Structural Equation Modeling (SEM), with limited exploration of dynamic SEM. Yet, dynamic SEM was essential, as it enhanced the precision of real-time consumer behavior prediction.
Objectives: This study critically examined recent advances in dynamic SEM, focusing on their effectiveness in improving predictive accuracy, model efficiency, and adaptive decision-making in response to temporal variations in consumer behavior.
Design/methodology/approach: A review of peer-reviewed empirical studies published between 2010 and 2025 was conducted. Using predefined inclusion and exclusion criteria, relevant works were retrieved from Scopus and Web of Science. Comparative synthesis highlighted differences between traditional and dynamic SEM applications.
Findings/Results: The results demonstrate that dynamic SEM substantially outperforms traditional SEM by incorporating temporal dynamics, capturing interindividual variations, and effectively managing intensive longitudinal data. Its strength lies in analyzing large-scale, high-frequency datasets from digital platforms such as Google Analytics, enabling accurate prediction and monitoring of consumer behavior over time. The study further contributes original constructs - including behaviorally relevant triggers, sentiment indicators, personalization measures, and engagement metrics - thus extending the scope of consumer analytics.
Conclusion: Dynamic SEM was shown to exert a transformative impact on consumer behavior research and marketing management by supporting real-time behavioral adjustments and agile decision-making. However, challenges remained regarding its computational capacity with large and complex datasets, underscoring the need for advanced data governance and sophisticated analytical tools.
Originality/value: The study evaluated the methodological innovations in a unique and systematic way and gave an advice on how to improve the SEM applications and theory when handling large and complex datasets when dealing with the temporal changes in consumer behavior. Researchers, policy-makers and practitioners were given the actionable recommendations on how to improve and utilize the dynamic SEM as a future-proof marketing analytics approach.

Keywords: big data analytics, dynamic structural equation modelling, latent growth modeling, marketing decision-making, temporal dynamics

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INTRODUCTION

Traditional Structural Equation Modeling (SEM) had long been a cornerstone in marketing research for analyzing consumer behavior and testing theoretical relationships. Its strength lied in the ability to simultaneously examine multiple variables and complex causal pathways within a single model. This made traditional SEM highly useful for validating conceptual frameworks and hypotheses (Ghasemy et al. 2020; Westland, 2015; Hair & Alamer, 2022). However, a critical limitation of traditional SEM was its static nature – it was typically applied to cross-sectional or aggregated data, and thus struggles to capture rapid or time-varying changes in consumer behavior. In today's digital environment, consumer preferences and actions could shift instantaneously in response to stimuli such as real-time advertisements, dynamic pricing, flash sales, or viral social media trends (Iskamto & Gunawan, 2023; Mobaderi et al. 2025). The rise of the big data era had further transformed consumer behavior analysis, providing vast streams of high-frequency data (text, video, click-streams, sensor data, etc.) from sources like e-commerce platforms, social media, and mobile apps (Juju & Arizal, 2023; Mehedintu & Soava, 2022). These data offered unparalleled insights but also exhibit high velocity and variability, challenging traditional analytical methods. As a result, real-time marketing analytics demanded more advanced methodologies that could accommodate temporal complexity and continuous data flow. Traditional SEM, being ill-suited for capturing fast shifts and longitudinal nuances in behavior, might yield models with reduced predictive accuracy and potential misinterpretation of relationships when applied to dynamic contexts. This shortcoming motivated the need for new approaches that could adapt to the temporal dynamics of modern consumer behavior.

Dynamic Structural Equation Modeling (dynamic SEM) has become a highly effective alternative to static models by including time as one of the most important dimensions, such that one can examine changing relationships in real-time consumer behavior (Dash & Paul, 2021; Kim et al. 2022). This dynamic perspective comes into particular significance in online environments where interactions take place with considerable frequency. Advances have broadened the range of applications, particularly with Bayesian estimation methods refining parameter precision and revising estimates based on new information, and are particularly useful for large-scale real-time applications (Dash & Paul, 2021; Kim et al. 2022). Web-based tools like Mplus, LISREL, and R packages have made possible the effective management of large-scale, high-frequency datasets (Hamaker, Asparouhov, & Muthén, 2021). Sophisticated fit indices (e.g., dynamic RMSE, MAE, CFI, TLI) and latent growth modeling (LGM) enable the accurate assessment of interindividual differences and behavioral trajectories (Dash & Paul, 2021; Zhang et al. 2024). Empirical evidence confirms dynamic SEM's superiority in modeling constantly changing variables and generating fine-grained insights (Hamaker et al. 2021; Dash & Paul, 2021; Liu, Bai, & Elsworth, 2024). However, despite growing adoption in psychology and finance (McNeish & Hamaker, 2020; Andriamiarana et al. 2023), marketing research still lags behind, with only modest integration of these methods (Magasi, 2025; Wairimu, 2023). This gap underscores the novelty and significance of the present study, which applies dynamic SEM innovations to the pressing needs of real-time marketing analytics (Liu, Bai, & Elsworth, 2024). In extending the frontiers of methodological research, the paper contributes to theoretical literature and practical applications and offers researchers and marketers paradigm-expanding tools for predicting consumer behavior in the new digital era.

In response to the lack of methodology in the real-time capture of consumer dynamics, the current research deploys a comprehensive approach. It commences by summarizing recent empirical and methodological advances in dynamic SEM, integrating principal findings on varying constructs, methods, and innovations (Dash & Paul, 2021; Hamaker et al. 2021; Praditya & Purwanto, 2024; Liu et al. 2024). Then it follows a comparative assessment of static SEM and dynamic SEM in the modeling of real-time consumer behavior. While static SEM is based on aggregate or static information, dynamic SEM uses high-frequency or streaming information and captures unfolding behaviors better. Comparisons are noted for forecasting precision, responsiveness, and risk of misinterpretation. Illustrative cases, like the modeling of consumer sentiment under the coverage of viral promotions, indicate where static SEM is weak and where dynamic SEM can deliver added value. The method also accounts for practical challenges in implementing dynamic SEM, including convergence issues, model misspecification, and estimate instability (Xu et al. 2020). Computational demands and data complexities are addressed through preprocessing, quality control, and integration practices (Kruschke, 2015; Zhu, Raquel, & Aryadoust, 2020). Techniques such as validation checks, audits, and standardized data formats help ensure consistency. Furthermore, leveraging advanced computing resources and cloud-based parallel processing alleviates the heavy demands of dynamic models (Hamaker, Asparouhov, & Muthén, 2021).

This research pursues multiple objectives aimed at addressing gaps in consumer behavior modeling. The primary goal is to establish the case for dynamic SEM in marketing research by highlighting the limitations of traditional SEM, especially its inability to capture temporal dynamics in real-time consumer behavior. This involves critically evaluating static assumptions and emphasizing the need for adaptive models capable of handling complex consumer data streams. Another purpose is to review recent methodological and technological innovations - such as Bayesian estimation, multilevel time-series modeling, machine learning integration, and ecological momentary assessment - that have enhanced dynamic SEM's flexibility and accuracy (Dash & Paul, 2021; Kim et al. 2022; Praditya & Purwanto, 2024). The study also explores broader managerial and entrepreneurial implications. Dynamic SEM facilitates agile, real-time decision-making, personalized marketing, and enhanced customer engagement, thereby improving competitiveness in digital markets (Juju & Arizal, 2023; Nayyar, 2022). By bridging theory and practice, this study advances scholarly debate and equips practitioners with actionable strategies for leveraging big data technologies in consumer analytics.

METHODS

This research was based entirely on secondary information extracted from peer-reviewed journal articles and scholarly reports published on the application of traditional and dynamic Structural Equation Modeling (SEM) to the behavior of consumers. The study included only the empirical research which were retrievable and with rigor research methodologies. The research covered and critically analyzed peer-reviewed literature of empirical studies published between 2010 and 2025 and afterwards traditional and dynamic SEM applications were compared from the synthesis done. Screening of studies was done using the pre-established inclusion and exclusion criteria. The data were retrieved from reputable online databases such as Scopus and Web of Science. Inclusion of studies in the specified temporal range helped to account for the dynamic nature of online consumer behavior and the ability for real-time analytics in the information-based marketplace.

The data collection process followed a thorough and structured literature review. Before starting, clear inclusion and exclusion criteria were set to maintain methodological rigor. Studies were included if they were empirical, had full-text access, used either traditional or dynamic SEM methods, focused on consumer behavior or marketing analytics, and specifically modeled time-sensitive or real-time data. Any publications lacking clear methodology, theoretical relevance, or accessibility were excluded. As shown in Figure 1, this selection framework was crafted to align with the study's focus on comparing methods and understanding the real-world applications of SEM in dynamic environments.

To meet the goals of the study, a three-part analytical approach was used. First, the latest developments in dynamic SEM were explored by critically examining academic literature. Special focus was given to new innovations like time-varying parameters, time-lagged effects, Bayesian estimation techniques, and the use of machine learning. This exploration was carried out using a qualitative synthesis that highlighted methodological strengths and practical applications found in the research. Second, the study looked at how dynamic SEM had been applied in real-world scenarios, particularly in analyzing consumer behavior in fast-moving and digital settings. This part centered on how the model helped with marketing strategies, behavior monitoring, and improving predictive accuracy. Third, a direct comparison was made between traditional SEM and dynamic SEM, looking at their theoretical bases, flexibility in analysis, and key performance indicators like model fit, explanatory strength, and prediction responsiveness. The aim was to highlight the benefits and drawbacks of each method and provide guidance on when and how each should be used in practice.

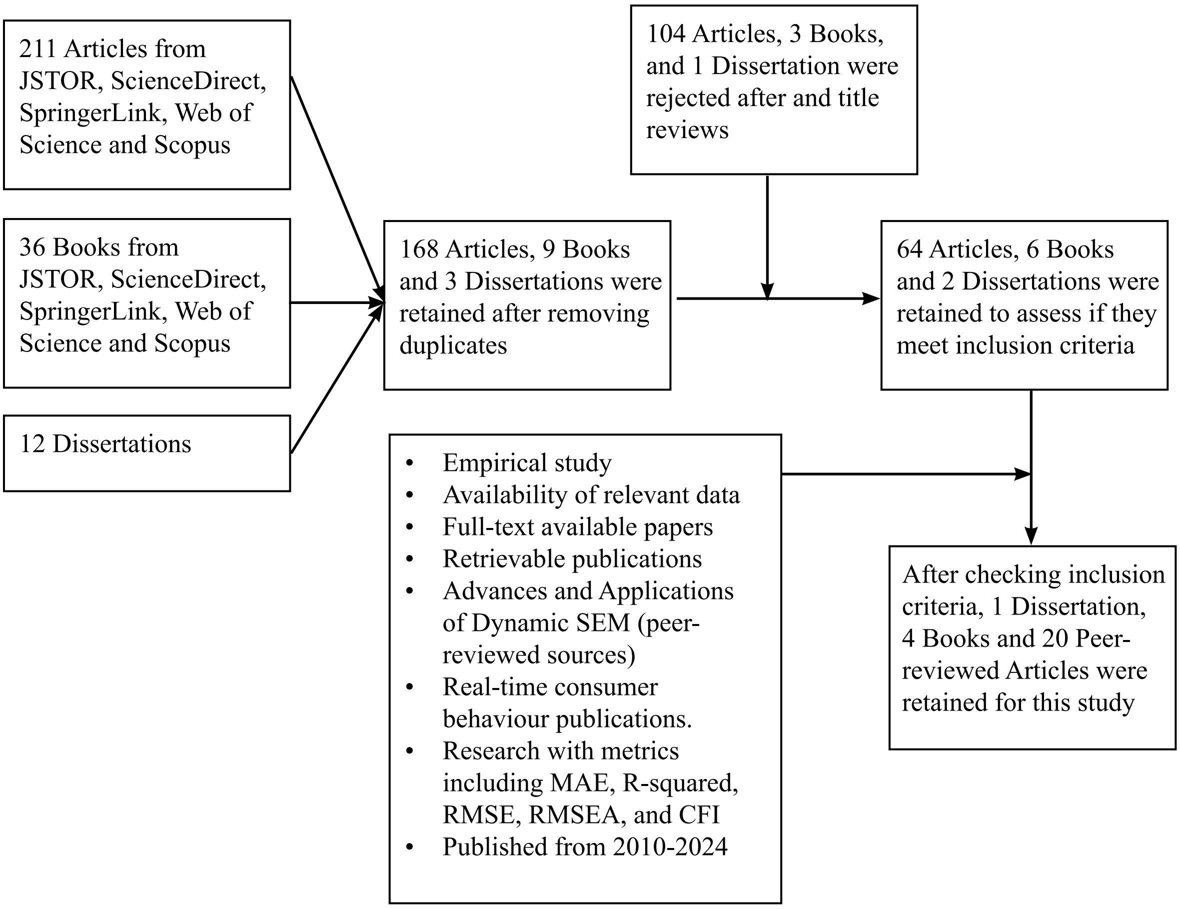

Figure 1. Established Inclusion Criteria

While this study is primarily exploratory and analytical, it operates on the core belief that dynamic SEM has a stronger ability to model real-time consumer behavior than traditional SEM. This belief is supported by both theoretical insights and advancements in technology noted in recent empirical research. As a result, the central hypothesis driving this investigation is as follows:

Ho: Dynamic Structural Equation Modeling (SEM) does not offer greater adaptability over time or more accurate predictions than traditional SEM when analyzing real-time consumer behavior. **Ha:** Dynamic Structural Equation Modeling (SEM) does offer greater adaptability over time and more accurate predictions than traditional SEM when analyzing real-time consumer behavior. Rather than testing this hypothesis using new data, the study evaluates it through a careful review and comparison of existing empirical research.

The foundation of this study presents consumer behavior modeling as a process shaped by both the analytical approach and the data environment. Traditional Structural Equation Modeling (SEM) treats relationships as fixed and relies on cross-sectional or summary data for calibration. On the other hand, dynamic SEM incorporates time as a fluid and ongoing factor, allowing the model to track changes and shifting relationships as they happen. This shift in thinking is crucial in settings where consumer choices are affected by real-time marketing, online interactions, and rapidly evolving preferences. The framework compares traditional and dynamic SEM along three key dimensions: how quickly they respond to time, how well they adapt to data, and how accurately they predict outcomes. Through this comparison, the study shows that dynamic SEM is better suited to meet the analytical needs of modern consumer research than traditional SEM.

RESULTS

Comparative Analysis of Traditional and Dynamic SEM

Traditional SEM has long been a mainstay in the exploration of complicated relationships between variables. It deploys covariance matrices to estimate and test theoretical models by mainly emphasizing static relationships between observed and latent variables (Yu, Zaza, Schuberth, & Henseler, 2021). Traditional SEM is proficient in testing theoretical structures and static relationships, for instance, testing the effect of marketing strategies on brand loyalty in clearly defined constructs. Nonetheless, the use of static and aggregate information captured in equal intervals results in a host of disadvantages such as poor dynamic relationships capture, diminished prediction accuracy, possible wrong conceptualization of causal effects, inflexibility in the management of high-frequency information and the depreciation of the fit and performance of the model. Consequently, it hides in full view dynamic movements of consumer behaviour and interplay (McNeish & Hamaker, 2020). Consumer preferences can, for instance, drastically change in response to technological development, social and cultural pressure, psychology, promotion and advertisement, policies and regulations and demographical changes, which are not captured by static data approach and may not register real-time transformations correctly (Thakkar, 2020).

In contrast, Dynamic SEM composes of new innovations that substantially enhance its capability to analyze complex, temporal and time dependent data (Dash & Paul, 2021; Penagos & García, 2024; Praditya & Purwanto, 2024). Among these innovations are Bayesian Estimation Methods for enhanced and refined parameter accuracy, Multilevel Time-Series Analysis to model nested data for longitudinal studies structures, and Ecological Momentary Assessment (EMA) for real-time behavioural tracking and analysis. Others are Machine Learning Integration which significantly improves predictive capabilities using AI-driven algorithms, while Cloud-Based Computing Forums which helps in large-scale datasets processing, enables large-scale data processing, improved Model Fit Metrics which substantially enhances precision using RMS, MAE and CFI metrics, and Real-Time Data Processing which improves dynamic modelling of continuously changing variables. These dynamic SEM advancements altogether improve model accuracy, adaptability and applicability across different research fields such as psychology and behavioural sciences (Penagos & García, 2024; Praditya & Purwanto, 2024). Dynamic SEM has the enhanced substantial advancement which incorporates time as a variable, facilitating to capture evolving interactions, using Latent Growth Modelling (LGM) to track individual trajectories of change and identify influential factors (Zhang, et al. 2024). For instance, LGM has been often utilized in consumer behavior research in tracking consumer preferences, analyzing brand loyalty, understanding purchase behavior evaluating advertising impact, studying psychological influences, assessing market segmentation and predicting customer retention (Penagos & García, 2024; Praditya & Purwanto, 2024; Zhi & Ha, 2024). This approach enables researchers to analyze and understand how to provide timely excellent services and satisfy customers across various service touchpoints and create long-term relationships with consumers.

Future Directions for Dynamic SEM in Consumer Analytics

Dynamic SEM increasingly is integrating machine learning a logarithms and artificial intelligence (AI) to its features to enhance predictive accuracy and real-time consumer behaviour datasets analysis from the digital platforms (Zhang & Chang, 2021; Memon et al. 2021; Katragadda, 2022) to improve the marketing strategies and enhance deep understanding of consumer motivations, behaviours and preferences (Hamaker et al. 2021). The dynamic SEM approach captures and analyses real-time consumer behaviour data from online platforms such as online marketplace, e-commerce, learning and education forums and social media (Bolton et al. 2018; Mobaderi et al. 2025) to facilitate businesses adapt and customize their marketing, operational efficiency, customer engagement, and innovation strategies in response to the immediate captured consumer feedback (Zhang & Chang, 2021; Memon et al. 2021; Katragadda, 2022). The model is also greatly utilised in big data analytics necessitating organizations to capture consumer preferences, attitudes, consumer behavioural trends, decision making factors, and pain points and challenges. Furthermore, dynamic SEM is progressively applied in longitudinal studies to handle intensive longitudinal data, capture capturing temporal dynamics, modelling latent variables, and improving accuracy in predicting consumer purchasing behaviour (Hamaker et al. 2021; Zhi and Ha, 2024).

Dynamic SEM depends on several performance metrics to assess model accuracy, fit, and predictive strength. These metrics include model fit metrics such as Root Mean Square Error of Approximation (RMSEA) (Zhang et al. 2022) which is used for evaluating model fit (Asparouhov et al. 2018). Comparative Fit Index (CFI) (Zhang et al. 2022) that measures model fit comparison, scale range, and adjustment of the sample size to improve the dynamic SEM model over a baseline (McNeish, Somers, & Savord, 2024), Tucker-Lewis Index (TLI) which adjusts for model complexity. Others are Bayesian Information Criterion (BIC) (Baral & Curran, 2023) that helps in appropriate model selection, and avoiding overfitting of data (Asparouhov et al. 2018). Others are Bayesian Estimation Metrics (Zhang et al. 2022) that help in improving parameter estimation, handling uncertainty, model comparison and predictive accuracy (Cross & Sheffield, 2019; Zhang et al. 2022; Magasi, 2025). Dynamic SEM is increasingly being combined with machine learning algorithms to analyse large-scale consumer datasets and AI-driven Bayesian estimation methods to improve model precision and adaptability. While advanced Bayesian methods refine longitudinal predictions, improving marketing strategies, the cloud computing platforms facilitate large-scale consumer datasets and analytics. This helps in effectively and efficiently to conduct real-time analytics without computational limitations. The dynamic SEM is being used to analyse social media engagement and e-commerce purchasing patterns and help organizations optimize personalized recommendations based on evolving consumer preferences. Moreover, future directions highlight the transformative potential of dynamic SEM in consumer analytics making it an important tool for giving quick time data to enable businesses to refine their marketing strategies (Zhang & Chang, 2021; Memon et al. 2021; Katragadda, 2022). Therefore, future advancements in Dynamic SEM should focus on enhancing computational efficiency, integrating AI-driven algorithms for better predictive analytics, and refining data collection methods to improve accuracy in consumer behaviours modelling. Consequently, organizations are adopting the dynamic SEM to optimize marketing strategies and improve consumer targeting.

Table 1 summarizes a comparative overview of traditional and dynamic SEM and future research direction implications. The table also illustrates the ability of dynamic SEM models to account for shifts in consumer behavior with the assistance of temporal variables that enable real-time marketing strategy adjustment and the need for quality, high-frequency data, thus highlighting the superiority of dynamic over traditional SEM models.

Table 1. A comparative framework of traditional and dynamic SEM

Aspect	Traditional SEM	Dynamic SEM
Introduction	Focuses on analyzing static relationships between latent variables through assessing covariance structures (Westland, 2015).	Integrates temporal dynamics, modelling the evolution of consumer behaviors over time (Hamaker et al. 2021).
Key Advances and Applications	Explore static theoretical models in consumer preferences and behaviour to offer relatively stable insights over time (Ghasemy et al. 2020).	Pioneering real-time analysis of consumer behaviour, providing immediate feedback and adaptable marketing strategies (Kronemann, 2022).
Methodological Foundations	Evaluate fixed and static theoretical relationships among variables based on both path analysis and factor analysis (Ghasemy et al. 2020; Dash & Paul, 2021).	Utilizes dynamic factor models, latent growth models, and state-space models to monitor real-time behavioral changes (McNeish & Hamaker, 2020; Dash & Paul, 2021).
Data Sources	Primarily relies on cross-sectional or longitudinal data, capturing static behavioral snapshots (Iskamto & Gunawan, 2023).	Requires high-frequency, real-time data from digital platforms such as e-commerce and social media (Tao et al. 2022).
Temporal Scope	Primarily retrospective, focusing on historical data or pre-set intervals for analysis (McNeish & Hamaker, 2020).	Offers predictive modelling, forecasting future consumer behaviors based on past and real-time data (Bolton et al. 2018).
Model Flexibility	Rigid model structure; most effective for environments with consistent and predictable behavior patterns (Ghasemy et al. 2020).	Highly flexible, allowing for the adaptation of models in response to rapidly changing consumer behaviors (Hamaker et al. 2021).

Table 1. A comparative framework of traditional and dynamic SEM (continue)

Aspect	Traditional SEM	Dynamic SEM
Real-time Data Adaptation	Unable to handle real-time data, limiting its use in fast-paced, evolving environments (Iskamto & Gunawan, 2023).	Built to process and react to real-time data, making it ideal for dynamic, fast-changing markets (Tao et al. 2022).
Time Sensitivity	Best suited for analyzing long-term trends; lacks real-time responsiveness (McNeish & Hamaker, 2020).	Highly time-sensitive, capable of providing continuous, real-time analysis and feedback (Kwasnicka et al. 2019).
Research Fit	Ideal for studies focusing on stable, long-term relationships and testing theoretical models with static data (Westland, 2015).	Best for research requiring real-time behaviour tracking, especially in dynamic industries (Bolton et al. 2018).
Software and Tools	Supported by tools like AMOS, LISREL, and EQS, which are suited for traditional, static data analysis (Hu & Lovrich, 2020).	Requires advanced software like Mplus and OpenMx to handle complex, dynamic data sets in real-time (Hu & Lovrich, 2020).
Real-World Applicability	Limited effectiveness in industries like e-commerce and social media, where consumer behaviors change rapidly (Mehedintu & Soava, 2022).	Highly applicable in digital marketing, app development, and other industries where consumer preferences shift quickly (Kronemann, 2022).
Applications in Marketing Research	Commonly used for analyzing stable, long-term consumer patterns and testing fixed hypotheses (Uju & Arizal, 2023).	Used extensively in real-time marketing to adjust campaigns dynamically based on evolving consumer behaviors (Kronemann, 2022).
Key Advantages	Well-suited for analyzing stable relationships, useful for theoretical model testing and validation (Westland, 2015).	Excels in tracking fast-changing behaviors, providing actionable insights in real-time for adaptive marketing strategies (Hamaker et al. 2021).
Conclusion and Future Directions	Remains valuable for static analysis, though less effective for dynamic, evolving behaviors (Ghasemy et al. 2020).	Expected to lead future research in real-time behaviour analysis, with potential for further advancements in computational techniques (Hamaker et al. 2021).

Objective three seeks to compare traditional SEM models and dynamic SEM techniques in representing their power to describe complex structures of the information. As can be noticed from Table 2, Dynamic SEM tends to perform better, with smaller measures of MAE and Root RMSE, mainly in the estimation of short-term behavioral and preference changes. Dynamic SEM tends to have larger R-squared measures and better fit indices, including Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), and Comparative Fit Index (CFI).

The numerical values in Table 2 convey various meanings regarding performance of two modelling methods. Dynamic SEM provides a threshold of less than 0.05 for significance. This has the implication of increased precision in dynamic SEM estimations over the traditional SEM which tends to reflect a threshold of over 0.10. This reflects the enhanced reliability of dynamic SEM. Moreover, the R-squared values portray the superiority of dynamic SEM. Dynamic SEM with numerical values of over 0.70 has enhanced power in explaining variance in the information. In contrast, traditional SEM has diminished explanation power. Validation of the fit of the metrics provides yet another superiority for dynamic SEM. The GFI and AGFI in favor of dynamic SEM exhibit values of over 0.90. Otherwise, traditional SEM fails to reach the standard with values of under 0.90. Likewise, the CFI reveals enhanced fit of the model for dynamic SEM which practically ranges over 0.90 while traditional SEM indicate suboptimum fit with values of under 0.90. Furthermore, RMSEA provides the evidence with dynamic SEM to generate low values which are under 0.05 reflecting on a well-fitting model in contrast with traditional SEM. The latter oversteps acceptable cutoff point of 0.08. Lastly, AIC and BIC reveal the recommendation where dynamic SEM has a more optimal modelling solution with low values under 80 in contrast with traditional SEM, exceeding over 100 in most situations. The results reflect the relevance of the use of dynamic SEM in research for proper modelling and understanding of variable interplay. Based on the comparative evidence and performance metrics, this study rejects Ho and accepts Ha, confirming that Dynamic SEM offers greater adaptability over time and more accurate predictions than Traditional SEM for real-time consumer behaviour analysis.

Table 2. Comparative analysis of performance metrics for traditional SEM and Dynamic SEM Models

Metric/Index	Traditional SEM	Dynamic SEM	Authors
Mean Absolute Error (MAE)	Higher MAE values, indicating less accuracy in prediction (e.g., > 0.10)	Lower MAE values (e.g., < 0.05), reflecting better accuracy in capturing changes	Browne & Cudeck (1992); Zhu et al. (2020)
Root Mean Squared Error (RMSE)	Higher RMSE (e.g., > 0.10), may not effectively capture short-term changes	Lower RMSE (e.g., < 0.05), particularly effective in predicting short-term fluctuations	Browne & Cudeck (1992); Mobaderi et al. (2025); Zhu et al. (2020)
R-squared (R^2)	Generally lower (e.g., < 0.50), indicating less explained variance	Typically, higher (e.g., > 0.70), indicating a better model fit to data	Schumacker & Lomax (2010); Zhu et al. (2020)
Goodness-of-Fit Index (GFI)	Values often < 0.90, indicating poorer fit	Values > 0.90; indicating good fit to the data	Bolton et al. (2018); Zhu et al. (2020)
Adjusted Goodness-of-Fit Index (AGFI)	Values often < 0.90	Values > 0.90; indicating better fit when adjusting for parsimony	Bolton et al. (2018); Zhu et al. (2020)
Comparative Fit Index (CFI)	Often < 0.90, indicating suboptimal fit	Values > 0.90; indicating strong model-data fit	Kruschke (2015); Zhu et al. (2020)
Root Mean Square Error of Approximation (RMSEA)	Values often > 0.08, indicating poor fit	Values < 0.05; indicating a well-fitting model	Browne & Cudeck (1992) ; Zhu et al. (2020)
Standardized Root Mean Square Residual (SRMR)	Often lacks consistency, higher values (e.g., > 0.10)	Typically, lower (e.g., < 0.08), reflecting the standardized difference between observed and predicted correlations	Kronemann (2022); Mehedintu & Soava (2022); Zhu et al. (2020)

Managerial Implications

The findings present notable managerial implications for executives in digital strategy and consumer analytics. In fast-changing, data-intensive markets where consumer preferences shift in response to dynamic pricing, viral content, or instant alerts, static models are inadequate. Dynamic SEM offers a methodological advance, providing real-time insights that enable swift strategic responses to market sentiment, campaign performance, and engagement patterns. This temporal sensitivity reduces reliance on outdated indicators and enhances decision agility. When combined with machine learning and Bayesian estimation, dynamic SEM further strengthens predictive accuracy and managerial foresight. Marketing practitioners can foresee the reaction of different groups of consumers to fluctuating stimuli and aid in micro-targeting and personal outreach strategies with the intention of optimizing the ratio of conversions and retention. Third, dynamic SEM enables the modelling of hierarchical and multilevel consumer data, such as behaviour patterns across different platforms (e.g., mobile vs. desktop) or geographic markets. Managers can use these insights to tailor regional or channel-specific strategies that maximize ROI. Lastly, dynamic SEM promotes a data-driven organizational culture. Grounding marketing analytics in temporal responsiveness and empirical rigor enables evidence-based decisions, fosters cross-functional collaboration, and equips teams to align their strategies with real-time shifts in consumer behaviour.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This study evaluated the progression of Dynamic Structural Equation Modelling (SEM) and its effectiveness in analysing real-time consumer behaviour compared with traditional SEM. By addressing theoretical and methodological gaps, the analysis confirmed dynamic SEM's superiority in predictive accuracy, temporal responsiveness, and adaptability. Incorporating time as a formative variable, dynamic SEM effectively captured the fluidity of consumer decision-making and leveraged high-volume datasets from platforms such as social media, e-commerce, and mobile applications. This enabled timely insights into engagement, sentiment, and behavioral shifts - critical for agility in fast-changing markets. Dynamic SEM was further reinforced by Bayesian estimation, multilevel time-series models, latent growth SEM, and machine learning, which improved parameter stability and reduced estimation bias. Fit indices such as RMSE, MAE, and CFI validated its robustness with real-time data. From a managerial perspective, dynamic SEM supported agile campaign adjustments, temporal segmentation, and anticipatory decision-making, transforming consumer analytics from retrospective to predictive systems.

Theoretically, this research advanced SEM scholarship by foregrounding temporal modelling and dynamic constructs, aligning with contemporary empirical contributions in big data contexts. Nonetheless, challenges persisted, including computational demands, pre-processing requirements, and convergence issues. Overcoming these would require user-friendly tools, cloud-based infrastructures, AI-driven optimization, and interdisciplinary collaboration among behavioural scientists, data experts, and marketers. In conclusion, dynamic SEM emerged as both a methodological breakthrough and a strategic instrument, enabling organizations to anticipate and adapt to consumer behaviour with greater clarity, accuracy, and flexibility in the digital era.

Recommendations

This study advances several recommendations for key stakeholder groups. For marketing practitioners and managers, dynamic SEM should be adopted as a core tool in analytics, moving beyond static approaches toward real-time, adaptive modelling of consumer behaviour. This requires investment in scalable data infrastructure to manage large, high-frequency inputs from social media, clickstreams, and IoT devices. Strong data governance - emphasizing pre-processing, standardization, and validation - must be prioritized to ensure accuracy and interpretability. Organizations should also upskill teams in platforms such as Mplus, R (dynr, lavaan), and Python for real-time analysis, while fostering collaboration among marketing, IT, and data science units to embed dynamic SEM into decision-making. For researchers and academics, expanding dynamic SEM applications is crucial. Potential areas include monitoring influencer effects and real-time brand perception. Hybrid approaches that integrate dynamic SEM with neural networks, reinforcement learning, or natural language processing can strengthen analysis of nonlinear and unstructured data. Closer links between SEM outputs and actionable metrics - such as engagement, churn, and lifetime value - are also encouraged. For policy-makers and educators, curricula should integrate dynamic modeling and time-sensitive analytics to align graduate skills with industry needs. Supporting open-source development and funding dynamic SEM tools will lower adoption barriers, particularly for smaller firms and academic institutions.

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