

Academic Articles

FROM FOUNDATIONS TO FRONTIERS: THE DEVELOPMENT AND FUTURE OF
STRUCTURAL EQUATION MODELING (SEM)

Taisith Kruasom^{1*}, *Sumalee Ngeoywijit*², *Sukhawit Sopapol*³,

*Tenatat Kosanlawit*⁴, *Sairoong Sangwarn*⁵, *Pichaya Adthajak*⁶

Faculty of Management Science, Ubon Ratchathani University^{1*,3,4,5}

*Freelance Academics Assistant Professor*²

*The Eastern University of Management and Technology*⁶

Email: taisith.k@ubu.ac.th^{1*}, *sumalee.n@ubu.ac.th*², *sukhawit.s@ubu.ac.th*³

*tenatat@yahoo.com*⁴, *sairoong.d@ubu.ac.th*⁵, *pichaya.a@umt.ac.th*⁶

Abstract

Structural Equation Modeling (SEM) is a versatile statistical framework for modeling complex relationships among observed and latent variables. This narrative review traces SEM's development from its foundational roots in factor and path analysis to its current integration with machine learning, Bayesian techniques, and big data analytics. We critically examine SEM's methodological advancements, including Confirmatory Factor Analysis (CFA), Multi-Group SEM, Bayesian SEM, and Dynamic SEM, and highlight its diverse applications across psychology, education, business, and health sciences. Emphasis is placed on current challenges—such as data quality, sample size, and model mis-specification—and future opportunities enabled by open-source tools and AI integration.

This review's objective is explicitly aligned with the article's purpose: to synthesize SEM's historical development, current methodologies, challenges, and future directions into practical guidance for researchers using SEM in increasingly complex data environments. This paper provides a comprehensive synthesis for both novice and experienced researchers, offering guidance on using SEM effectively in an era of increasingly complex data environments. This review benefits readers by providing practical insights into applying SEM in their current research, guiding them to select suitable model-fitting tools and interpret results effectively.

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* Corresponding author

Introduction

Structural Equation Modeling (SEM) is a powerful tool that helps researchers make sense of complex relationships in their data. By combining ideas from both factor analysis and path analysis, SEM allows us to explore how different concepts are connected, especially when some of those concepts, like attitudes or motivations, are not directly measurable. What makes SEM especially valuable is its flexibility: it is widely used in fields like psychology, education, business, and the social sciences because it can handle both theory and data in a way that is rigorous, yet adaptable (Kline, 2015; Byrne, 2016).

Structural Equation Modeling (SEM) has come a long way. What started as a blend of path analysis and factor analysis has grown into a sophisticated framework capable of handling increasingly complex research questions. Over the decades, SEM has evolved to include dynamic modeling techniques, broadening its ability to capture nuanced relationships in data. But this growth hasn't come without its challenges. Researchers have had to grapple with issues like securing adequate sample sizes, handling missing data, and carefully specifying and validating models (Bollen, 1989; Hoyle, 2012).

To tackle these hurdles, the field has embraced innovation. Techniques like machine learning, Bayesian modeling, and hybrid approaches are reshaping what's possible with SEM, moving it well beyond its traditional uses (van de Schoot et al., 2017). This paper explores the key turning points in SEM's development and the creative strategies scholars are using to adapt it for modern needs. Whether it's used to confirm psychological theories or map out consumer behavior, SEM remains a remarkably versatile and empowering tool for researchers navigating today's complex data landscape (Schumacker & Lomax, 2016; Muthén & Muthén, 2017).

Historical Progression of Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) boasts a rich and evolving history, tracing its roots to the early 20th century (see more in Table 1 and Figure 1). Over the decades, it has matured into a sophisticated and indispensable tool for multivariate analysis, underpinned by foundational theories, methodological advancements, and technological innovations. This evolution has significantly broadened its applicability across disciplines.

The origins of SEM can be traced to two pioneering statistical techniques: path analysis and factor analysis. Path analysis, introduced by Sewall Wright in 1921, provided a graphical framework for modeling causal relationships among observed variables (Wright, 1921). Wright's development of path diagrams formalized concepts such as direct, indirect, and total effects, offering researchers an analytical and visual method to explore complex systems. This innovation laid the foundation for SEM's structural component by enabling the decomposition of correlations into their constituent pathways.

Simultaneously, Charles Spearman's work on factor analysis in 1904 addressed the measurement side of SEM (Spearman, 1904). Spearman's groundbreaking "g-factor" theory of intelligence exemplified the use of factor analysis to uncover latent constructs underlying observed variables, such as cognitive abilities. Factor analysis introduced a rigorous methodology for validating latent variables through observable indicators, forming the bedrock of SEM's measurement component.

The 1970s marked a pivotal moment in SEM's development when Karl Jöreskog integrated these foundational techniques into a comprehensive statistical framework. His contributions culminated in the creation of the LISREL (Linear Structural Relations) software, co-developed with Dag Sörbom in 1978 (Jöreskog, 1970; Jöreskog & Sörbom, 1978). LISREL revolutionized SEM by allowing researchers to simultaneously test structural hypotheses (causal relationships) and measurement models (latent constructs), making the methodology more practical and accessible. Jöreskog also introduced model fit indices, such as the chi-square test, enabling researchers to evaluate the adequacy of their models. Additionally, his incorporation of latent variables with measurement error bridged theoretical constructs with empirical data, significantly advancing SEM's analytical rigor.

The 1980s and 1990s witnessed significant refinements in SEM methodologies. Scholars such as Kenneth Bollen and Peter Bentler contributed advanced goodness-of-fit indices, including the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Tucker-Lewis Index (TLI) (Bollen, 1989; Bentler, 1990). These indices addressed the limitations of traditional chi-square tests, which were often overly sensitive to sample size. Methodological advances during this period also included robust estimation methods, such as Weighted Least Squares (WLS), which accommodated violations of normality and small sample sizes (Muthén, 1984). The development of multigroup SEM enabled comparisons across populations, while longitudinal SEM facilitated the analysis of change over time through techniques like latent growth curve modeling (Bollen & Curran, 2006).

Technological advancements further propelled SEM during this era. User-friendly software such as AMOS provided graphical interfaces that democratized SEM for less technical users (Arbuckle, 1995), while platforms like EQS and Mplus introduced innovative features, including Bayesian estimation and multilevel modeling capabilities (Bentler & Wu, 1995; Muthén & Muthén, 2017). These tools greatly expanded the accessibility and utility of SEM for researchers across a variety of disciplines.

In the 21st century, SEM continues to evolve, driven by computational advances and the increasing complexity of research questions. One of the most transformative developments has been the integration of SEM with big data and machine learning. Hybrid models that merge SEM's theory-driven approach with machine learning's predictive capabilities enable researchers to analyze large, high-dimensional datasets (Shmueli et al., 2016). For example, SEM is now applied in genomics to model genetic pathways affecting disease outcomes and in social network analysis to examine latent influencer behaviors

within communities. In artificial intelligence, SEM contributes to explainable AI by providing interpretable models of relationships within neural networks (Pearl, 2000).

Dynamic SEM represents another recent innovation, enabling the modeling of time-varying relationships and feedback loops. These capabilities are particularly valuable in fields like neuroscience, where understanding dynamic interactions is crucial, and environmental science, where systems often exhibit complex temporal dependencies (Asparouhov et al., 2018). Furthermore, open-source tools, such as the R package *lavaan*, have democratized SEM by providing powerful analytical capabilities at no cost, expanding access to researchers in resource-constrained settings (Rosseel, 2012).

Today, SEM's cross-disciplinary applications extend its impact to fields such as climate science and artificial intelligence, where modeling dynamic relationships and latent variables is crucial for addressing complex systems. From its origins in path and factor analysis to its integration with advanced computational methodologies, SEM has demonstrated remarkable adaptability and methodological rigor. Its versatility and ongoing innovation ensure its enduring role as a cornerstone of multivariate analysis, equipping researchers with the tools necessary to address the increasingly complex questions of modern science. In Thailand, SEM has been increasingly adopted across education, psychology, public administration, and business research. Researchers commonly employ AMOS, LISREL/Mplus, and SmartPLS to model latent constructs behind behavioral and organizational phenomena; this review highlights practical entry points—model specification, fit assessment, and reporting—that Thai scholars can apply directly to ongoing projects (Santoso et al., 2025; Mustafa et al., 2020; Fathema et al., 2015).

Table 1 Key Milestones in SEM's Historical Progression

Era	Milestone	Significance
Early 20th Century	Development of path analysis and factor analysis	Established the foundations for studying causal relationships and latent constructs.
1970s	Integration of path and factor analysis by Jöreskog; development of LISREL software.	Formalized SEM as a unified statistical methodology and provided practical tools for implementation.
1980s-1990s	Introduction of robust estimation methods, goodness-of-fit indices, and multigroup/longitudinal SEM.	Expanded SEM's methodological rigor and versatility across diverse research fields.
Present Day	Integration with machine learning, big data analytics, and the development of dynamic SEM techniques.	Broadened SEM's applicability to modern, interdisciplinary research challenges.

Objective of the Research

To provide a comprehensive review that is fully aligned with the article’s purpose—synthesizing SEM’s historical development, methodological advancements, current challenges, and future directions into actionable guidance for research and practice.

Research Methodology

This study adopts a narrative literature review approach, drawing on secondary academic sources to synthesize the evolution and applications of SEM in various disciplines.

Milestones in the Historical Progression of SEM

The historical progression of SEM reflects its transformation from an independent statistical technique into a cornerstone of multivariate analysis. From Wright’s path analysis and Spearman’s factor analysis to Jöreskog’s formalization in the 1970s and modern computational innovations, SEM has consistently evolved to meet the needs of complex research questions. Its ability to adapt to new methodologies and technologies ensures its continued relevance and growing impact across disciplines.

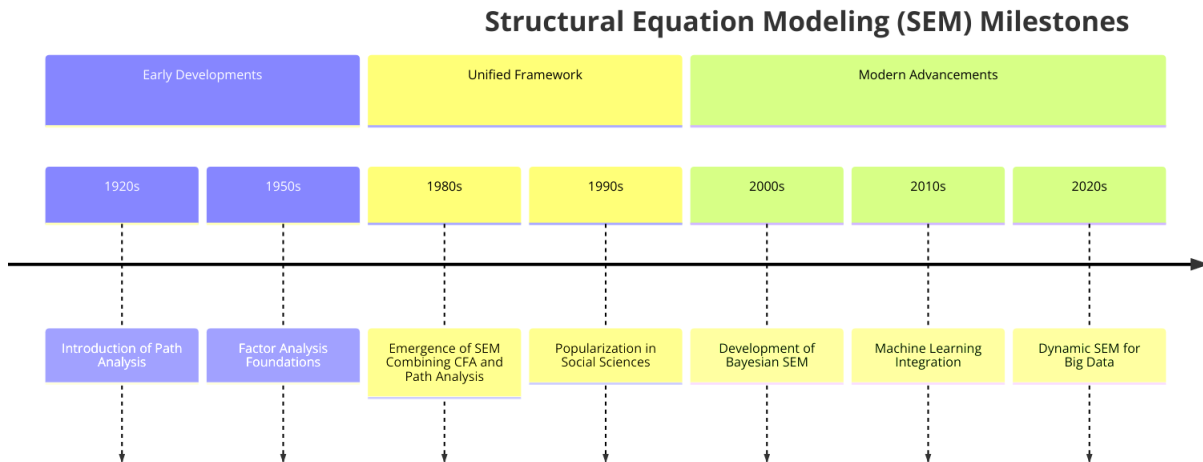


Figure 1 Structural Equation Modelling (SEM) Milestones (Authors)

Methodological Developments and Applications of SEM

The methodological advancements in Structural Equation Modeling (SEM) have significantly expanded its utility and precision, allowing researchers to address increasingly complex research questions. These developments have not only refined the technique but also broadened its applicability across various fields.

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a fundamental component of Structural Equation Modeling (SEM), widely used for validating the structure of latent constructs in research. Unlike Exploratory Factor Analysis (EFA), which identifies potential factor structures without predefined assumptions, CFA explicitly tests relationships between observed indicators and theoretical constructs based on prior hypotheses (Byrne, 2010). This key distinction positions CFA as a critical tool for researchers aiming to confirm the validity of their theoretical frameworks.

The primary objective of CFA is to assess construct validity by examining whether the observed variables accurately represent the underlying latent variables. This is achieved with fit indices, such as the Root Mean Square Error of Approximation (RMSEA) and the Comparative Fit Index (CFI), which evaluate how well the hypothesized model aligns with the empirical data (Kline, 2015). By providing quantitative measures of model fit, CFA ensures that the specified relationships between variables are consistent with the observed data, reinforcing the reliability of the measurement model.

CFA has broad applications across multiple disciplines. In psychology, it is commonly used to validate scales for measuring constructs such as anxiety, motivation, and personality traits (Byrne, 2010). In education, CFA plays a crucial role in testing the structure of standardized tests and assessment instruments, ensuring that they measure the intended constructs accurately (Little, 2013). Similarly, in business, CFA is instrumental in developing customer satisfaction surveys and brand loyalty measures, enabling organizations to quantify intangible concepts with precision (Hair et al., 2021).

The significance of CFA lies in its ability to ensure measurement precision. By rigorously testing the validity of latent constructs, CFA provides a solid foundation for subsequent structural analysis. This precision not only enhances the credibility of research findings but also enables researchers to develop reliable and interpretable models for examining complex relationships among variables. As a result, CFA remains an indispensable tool in the methodological arsenal of researchers across various fields.

Multi-Group SEM

Multi-Group Structural Equation Modeling (MG-SEM) is a powerful extension of traditional SEM that allows researchers to examine whether relationships among variables hold consistently across different groups, such as gender, age, cultural backgrounds, or socioeconomic strata. This capability is

essential for evaluating whether psychological constructs, interventions, or theoretical models function similarly across diverse populations (Kline, 2015; Byrne, 2010).

At the heart of MG-SEM is measurement invariance testing, a methodological step that ensures the constructs are interpreted similarly across groups. Without establishing invariance, observed differences in structural relationships might stem from measurement artifacts rather than true group-level variation. As highlighted by Steenkamp and Baumgartner (1998), overlooking invariance can lead to misinterpretation, potentially invalidating cross-group comparisons.

Measurement invariance is typically tested in three hierarchical stages. First, configural invariance tests whether the basic factor structure is consistent across groups—essentially, whether people across groups conceptualize the construct similarly. Next, metric invariance examines whether the strength of relationships between latent variables and their indicators is equivalent, indicating that scale items carry the same meaning across groups. Finally, scalar invariance tests whether group means can be meaningfully compared by checking the equality of intercepts (Kline, 2015; Byrne, 2010).

Once measurement invariance is established, researchers can assess structural invariance, which investigates whether the relationships among latent constructs differ between groups. This allows for targeted exploration of questions such as: *Does a stress-coping model function similarly in men and women?* or *Do socioeconomic factors affect academic performance differently across cultural settings?*

The applications of MG-SEM are comprehensive and meaningful. In cross-cultural psychology, for instance, MG-SEM is used to evaluate whether constructs like well-being or identity development manifest similarly across countries or cultural groups (Steenkamp & Baumgartner, 1998). In education, MG-SEM supports the analysis of how teaching practices or school climate may affect students differently based on socioeconomic status or language background (Little, 2013). In policy and program evaluation, MG-SEM enables researchers to compare intervention outcomes across different populations or regions, ensuring that policies are equitable and appropriately tailored to local contexts (Byrne, 2010).

Importantly, MG-SEM is supported by widely used software packages such as AMOS (Arbuckle, 1995), Mplus (Muthén & Muthén, 2017), and *lavaan* in R (Rosseel, 2012), which offer increasingly user-friendly frameworks for testing invariance and comparing models across groups.

In conclusion, Multi-Group SEM is indispensable for researchers seeking to ensure measurement fairness and uncover meaningful group-level insights. By rigorously establishing whether constructs operate equivalently across populations, MG-SEM safeguards the validity of cross-group comparisons and informs more inclusive and data-driven policies, programs, and theoretical frameworks.

Bayesian SEM

Bayesian Structural Equation Modeling (SEM) represents a major step forward in the evolution of SEM methods. What sets it apart is its use of *prior knowledge* in the estimation process—something that traditional Maximum Likelihood (ML) estimation methods simply don't do. While ML relies entirely on the data at hand, Bayesian SEM blends prior distributions with observed data to estimate parameters, producing *posterior* distributions that reflect both existing knowledge and new evidence (Muthén & Asparouhov, 2012). This makes it especially valuable when researchers are working with small samples, complex models, or data that don't meet the typical assumptions of normality.

One of the biggest advantages of Bayesian SEM is its resilience under challenging data conditions. Whether you're working with small samples, skewed data, or intricate models with many parameters, Bayesian methods can help stabilize estimates by drawing on prior distributions (van de Schoot et al., 2017; Lee & Song, 2004). This makes it particularly useful in fields like clinical psychology or healthcare, where collecting large datasets is often difficult or even impossible. For example, in studies on rare diseases or early-phase clinical trials, Bayesian SEM provides a way to draw meaningful conclusions from limited data (Muthén & Muthén, 2017).

Bayesian SEM also has important applications in education, especially in classroom-based research where participant numbers are inherently small. When evaluating a new teaching method in a single school or small district, researchers can still produce reliable estimates by incorporating informed priors, such as data from previous studies or expert judgment (Little, 2013). Similarly, in exploratory or preliminary studies, Bayesian SEM allows researchers to explore hypotheses in underrepresented populations or pilot datasets, helping to build the groundwork for future, larger-scale research (Hair, Black, Babin, & Anderson, 2021).

Another notable strength of Bayesian SEM is its transparency. Because the approach yields full posterior distributions for each parameter, researchers can assess uncertainty more comprehensively than with point estimates alone. This enhances interpretability, which is especially important when making decisions in policy, healthcare, or business contexts (Pearl, 2000).

In sum, Bayesian SEM brings a level of flexibility and robustness that significantly expands the toolkit of researchers. By accommodating small samples, handling non-normal data, and offering rich insights into parameter uncertainty, it opens the door to high-quality modeling in situations that might otherwise be analytically impossible. As research becomes more data-driven—but also more complex and resource-constrained—Bayesian SEM is poised to play an even more critical role in helping scholars make the most of their data.

Dynamic SEM

Dynamic Structural Equation Modeling (SEM) marks a significant evolution of traditional SEM by introducing a temporal dimension into the analysis of structural relationships. While conventional SEM assumes static associations among variables, Dynamic SEM (DSEM) models how these relationships change and interact over time. This innovation is especially valuable in research contexts where understanding development, feedback mechanisms, or time-based changes is central (Bollen & Curran, 2006; Asparouhov, Hamaker, & Muthén, 2018).

A defining strength of Dynamic SEM is its ability to handle lagged effects, autoregressive patterns, and dynamic feedback loops. These features enable the modeling of how earlier states of variables influence later outcomes, facilitating the exploration of both direct and indirect pathways across time points (Little, 2013; Muthén, 1984). As a result, researchers gain a deeper, more accurate understanding of causal processes that unfold incrementally, rather than instantaneously.

The applications of DSEM span several disciplines. In developmental psychology, DSEM allows for nuanced modeling of human development, such as tracking emotional regulation or cognitive growth across childhood and adolescence (Little, 2013; Biesanz, 2012). Researchers can examine how earlier developmental milestones influence later outcomes while accounting for feedback between behavioral and environmental variables over time.

In educational research, DSEM is used to study longitudinal learning processes and the impact of educational interventions across semesters or academic years. This approach has been instrumental in understanding how instructional design, curriculum modifications, or even socio-economic variables affect learning trajectories over time (Byrne, 2010; Hair, Black, Babin, & Anderson, 2021).

In business and marketing, DSEM provides insights into evolving consumer behavior. By modeling longitudinal customer data, firms can analyze how satisfaction, loyalty, and brand perception change in response to marketing strategies or competitive dynamics (Shmueli, Ray, Velasquez Estrada, & Chatla, 2016). This allows businesses to optimize strategic decision-making based on the temporal patterns of consumer engagement.

Methodologically, Dynamic SEM incorporates foundational principles from early SEM research while extending them through integration with time series analysis and Bayesian statistics. Muthén and Asparouhov (2012) and van de Schoot et al. (2017) emphasize the flexibility of Bayesian frameworks in handling complex dynamic models, especially when data are limited or hierarchical. Tools such as Mplus (Muthén & Muthén, 2017), *lavaan* in R (Rosseel, 2012), and AMOS (Arbuckle, 1995) now support dynamic modeling, reflecting its growing integration into mainstream SEM practice.

The theoretical underpinnings of DSEM are rooted in foundational work by Jöreskog (1970), Bollen (1989), and Wright (1921), who conceptualized causal paths and recursive systems long before

modern computational tools made dynamic modeling feasible. These early innovations laid the groundwork for current applications that incorporate feedback, temporal variation, and system dynamics.

In sum, Dynamic SEM is an indispensable tool for exploring longitudinal processes and causal dynamics across time. By capturing the evolution of relationships, DSEM enhances both the explanatory power and validity of research findings. As complex, time-dependent questions continue to emerge across psychology, education, and business, Dynamic SEM stands out as a crucial methodology for advancing interdisciplinary research and understanding systems in motion.

Applications Across Fields

The continuous methodological advancements in Structural Equation Modeling (SEM) have solidified its place as a critical tool for data analysis across a broad spectrum of academic and professional disciplines. Its flexibility in integrating latent and observed variables, modeling complex relationships, and accommodating multiple levels of analysis has made SEM particularly powerful in addressing nuanced and multifaceted research questions.

In psychology, SEM is widely used to examine behavioral and emotional processes. Its ability to simultaneously model direct and indirect effects enable researchers to explore complex pathways linking psychological constructs such as stress, coping strategies, and mental health outcomes. For example, SEM allows for the detailed analysis of how internal psychological factors interact with external stressors to influence well-being, which can guide the development of targeted interventions (Byrne, 2010; Bollen, 1989). The technique's ability to incorporate latent variables also supports the modeling of abstract concepts like anxiety or motivation with greater precision (Kline, 2015).

In the education sector, SEM plays a vital role in evaluating instructional effectiveness and student learning outcomes. Researchers often use SEM to investigate how latent factors like student engagement, self-efficacy, or perceived support influence academic performance. This is particularly useful for assessing the efficacy of teaching methods or curriculum interventions in fostering academic achievement (Little, 2013; Hair et al., 2021). By uncovering indirect effects and mediating relationships, SEM enables a comprehensive understanding of the educational experience, guiding policy and pedagogical improvements.

The business world has also embraced SEM for its capacity to inform strategic decision-making. Companies use it to examine the relationships among marketing efforts, customer satisfaction, brand perception, and consumer loyalty. SEM is especially valuable when assessing mediation or moderation effects within customer journey models, such as determining whether customer service quality mediates the link between product features and brand loyalty (Hair et al., 2021; Shmueli, Ray, Velasquez Estrada, & Chatla, 2016). These insights inform data-driven strategies that optimize customer engagement and business outcomes.

SEM has seen transformative methodological enhancements over the years. The integration of techniques like Confirmatory Factor Analysis (CFA) and Multi-Group SEM has advanced its utility for cross-group comparisons, enabling insights across cultures, organizations, or demographic segments (Cheung & Rensvold, 2002). Bayesian SEM, as described by van de Schoot et al. (2017), provides solutions for small-sample and high-parameter models by incorporating prior information, improving estimation stability. Dynamic SEM, a more recent innovation, facilitates the modeling of processes that unfold over time, offering critical insights in fields such as clinical psychology or longitudinal organizational research (Asparouhov, Hamaker, & Muthén, 2018).

The accessibility of SEM has also expanded through software platforms such as AMOS (Arbuckle, 1995), Mplus (Muthén & Muthén, 2017), EQS (Bentler & Wu, 1995), *lavaan* in R (Rosseel, 2012), and the long-standing LISREL framework (Jöreskog & Sörbom, 1978). These tools have made SEM more user-friendly and adaptable to a variety of data structures and research goals, further increasing its appeal to a diverse range of users.

Foundational work by SEM pioneers like Spearman (1904), Wright (1921), and Jöreskog (1970) laid the groundwork for its conceptual structure, while modern scholars like Pearl (2000) and Bollen and Curran (2006) have expanded its causal modeling and longitudinal capacities. These developments have not only broadened the scope of SEM but also reinforced its status as a rigorous and theory-driven approach.

In conclusion, SEM has become indispensable in psychological science, education, business analytics, and beyond. Its continuing evolution—driven by statistical innovation, enhanced software capabilities, and interdisciplinary applications—ensures that SEM will remain central to solving complex research problems in today’s data-rich environment. By connecting empirical evidence to theoretical frameworks, SEM empowers researchers and practitioners to make informed, meaningful contributions across domains.

Challenges in SEM

Structural Equation Modeling (SEM) continues to be a cornerstone of multivariate analysis, prized for its ability to examine intricate relationships among latent and observed variables. Yet, as powerful as SEM is, its effective use is not without hurdles. Challenges around data quality, model specification, sample size, and overreliance on model fit indices remain persistent, demanding thoughtful attention from researchers.

One of the most common and critical issues is data quality. Missing data, outliers, and violations of normality can severely compromise SEM results. When data are missing or non-normally distributed, parameter estimates become biased and standard errors unreliable. For example, Kang (2013) emphasizes that missing data must be addressed through robust strategies like multiple imputation or full information maximum likelihood (FIML) to avoid biased conclusions. Similarly, Rhemtulla, Brosseau-Liard, and Savalei

(2012) show that assuming continuity for categorical variables under suboptimal conditions can distort outcomes. Bootstrapping methods and simulation-based approaches, such as those described by Mair, Satorra, and Bentler (2012), can mitigate the effects of non-normality by producing robust standard errors and confidence intervals.

Another core challenge in SEM lies in model specification. Incorrectly specified models—whether due to omitted variables, improper structural paths, or flawed measurement models—can lead to invalid conclusions. Rhemtulla, van Bork, and Borsboom (2020) argue that poorly designed latent variable measurement models can introduce more error than simple measurement inaccuracies. The importance of aligning theoretical constructs with the model is echoed in Kline (2023), who stresses that theory, not fit indices, should drive model construction. Researchers are encouraged to employ methods like Exploratory and Confirmatory Factor Analysis (EFA/CFA) to test model structure before advancing to complex models.

Sample size limitations further complicate SEM, particularly when dealing with models that include latent interactions or nonlinear components. Small sample sizes can cause estimation failures and inflate the risk of convergence issues. Fortunately, recent developments in Bayesian SEM offer a promising alternative. These methods, as discussed by Muthén and Asparouhov (2012) and Lee and Song (2004), allow the incorporation of prior information to stabilize estimates when sample sizes are limited. Moreover, alternative estimation techniques—such as the LMS method (Klein & Moosbrugger, 2000) or quasi-maximum likelihood approaches (Klein & Muthén, 2007)—are especially useful for modeling interaction effects in smaller or less-than-ideal datasets.

A further complication is the overreliance on fit indices like RMSEA, CFI, and TLI. While these tools are important for assessing how well a model fits the data, putting too much weight on them can encourage overfitting or model tweaking for statistical rather than theoretical reasons. As Marsh, Wen, and Hau (2004) argue, excessive emphasis on statistical fit can obscure theoretical inconsistencies. A more balanced approach—one that incorporates theoretical rationale and replicability—is necessary. Cross-validation, replication, and external model comparisons can enhance generalizability and prevent tailoring models to peculiarities in a single dataset (Schoemann & Jorgensen, 2021).

Furthermore, increasing attention is being paid to nonlinear and latent interaction models, which present both opportunities and challenges. Scholars like Kenny and Judd (1984), Jöreskog and Yang (1996), and Kelava and Brandt (2022) have shown that modeling interactions among latent variables requires advanced estimation strategies and often larger sample sizes. Innovative techniques like latent moderated structural equations (Maslowsky, Jager & Hemken, 2015) and the use of extended unconstrained approaches (Kelava & Brandt, 2009) provide promising solutions but add complexity that must be carefully managed.

In summary, SEM remains a robust and flexible tool for psychological, behavioral, and social sciences. However, its power is only fully realized when these methodological challenges are thoughtfully addressed. By using advanced estimation methods, applying rigorous theoretical reasoning, and balancing model fit with empirical grounding, researchers can ensure their SEM analyses yield valid, reliable, and replicable insights.

Emerging Opportunities in SEM

Recent advances in technology and methodology are breathing new life into Structural Equation Modeling (SEM), creating exciting possibilities for researchers across a range of disciplines. One major leap forward is the integration of SEM with machine learning techniques. These modern algorithms enhance SEM's traditional capabilities by automating model selection, improving predictive performance, and uncovering complex relationships that might be missed using conventional approaches. By blending theory-driven SEM with data-driven tools like decision trees or neural networks, researchers can construct hybrid models that go beyond the limitations of either method alone (Muthén & Asparouhov, 2012).

The big data revolution also aligns naturally with SEM's strengths. Because SEM can model latent constructs and handle complex structures, it's well-suited for analyzing high-dimensional datasets, such as those in genomics, marketing, or social networks. These areas often involve latent variables, interactions, and longitudinal patterns—all elements SEM can elegantly represent (Bollen, 2002; Hallquist & Wiley, 2018). This makes SEM a key player in exploring hidden patterns in massive datasets, from gene-environment interactions to customer segmentation in digital markets.

Moreover, SEM is expanding into fast-growing, cross-disciplinary fields such as climate science, artificial intelligence, and healthcare. For example, in environmental research, SEM helps scientists model feedback loops between climate indicators. In AI, SEM contributes to more interpretable models by making machine decision-making processes more transparent—an increasingly important goal in the era of explainable AI (Kelava & Brandt, 2022; Bollen & Bauldry, 2011).

Another promising development is the growing accessibility of SEM tools. Open-source software like the *lavaan* package in R has made advanced SEM techniques more available to researchers everywhere, not just those with access to expensive proprietary tools (Rosseel, 2012). This democratization of SEM promotes equity in science, allowing researchers from underfunded institutions and developing regions to engage in sophisticated modeling.

SEM has come a long way from its roots in path analysis and factor analysis (Bollen, 1989). As challenges like non-normal data, sample size limitations, and complex interactions persist (Bradley, 1978; Cham et al., 2012; Bollen, 1996), the adoption of new tools and techniques is helping SEM overcome its traditional constraints. From integrating Bayesian strategies (Gelman & Rubin, 1992; Brooks & Gelman, 1998)

to improving estimation in latent interactions (Brandt et al., 2020), SEM is adapting to meet the demands of modern research.

In sum, SEM's ability to evolve and connect theory with data continues to make it a go-to methodology for tackling today's toughest research questions. With ongoing innovations and broader accessibility, SEM is poised to remain a vital tool for driving scientific discovery across disciplines and around the globe.

Discussion

The evolution of Structural Equation Modeling (SEM) underscores its resilience and adaptability as a statistical methodology, consistently evolving to meet the demands of complex research challenges. By bridging theoretical constructs with empirical data, SEM has become an indispensable tool across diverse disciplines, including psychology, education, business, and healthcare (Kline, 2023; Bollen, 1989; Flora, 2018). Methodological advancements such as Confirmatory Factor Analysis (CFA) and Multi-Group SEM have enhanced its ability to validate constructs and compare models across populations (Brown, 2015; Koziol, 2023), ensuring its versatility in cross-cultural and demographic research.

Bayesian SEM has further expanded SEM's applicability to small and complex datasets, addressing traditional limitations while improving robustness (Asparouhov & Muthén, 2010; Ji et al., 2020; Brooks & Gelman, 1998). Similarly, Dynamic SEM empowers researchers to model time-dependent relationships, introducing a temporal dimension to analyses traditionally constrained by static approaches (Asparouhov, Hamaker, & Muthén, 2018; Hamaker et al., 2018).

Despite these significant advancements, challenges remain. Data quality issues, such as missing data, outliers, and non-normality, pose a threat to model validity (Astivia, 2020), while an overreliance on fit indices risks undermining theoretical integrity (McDonald & Ho, 2002; Boomsma, 2000). These challenges highlight the need for rigorous pre-analysis techniques and a balanced approach to model evaluation that integrates fit indices with robust theoretical frameworks (Maydeu-Olivares, 2017; Graham, 2008).

Addressing these limitations demands that researchers prioritize methodological rigor while embracing emerging methodologies, such as machine learning, to refine model selection, improve prediction accuracy, and enhance the reliability of SEM (Pearl, 2023; Wysocki, Lawson, & Rhemtulla, 2022).

Emerging opportunities in SEM underscore its growing relevance in the digital age. Integration with machine learning enhances its analytical power, enabling hybrid models that combine theory-driven and data-driven approaches (Hamaker & Wichers, 2017; Epskamp et al., 2018). Big data applications further expand SEM's scope, allowing researchers to analyze high-dimensional datasets in areas such as genomics, social network analysis, and marketing (Gelman, Hwang, & Vehtari, 2014; Ellington & Baruník, 2020). Moreover, the availability of open-source tools, such as the R package *lavaan*, democratizes access to

SEM, fostering inclusivity and enabling researchers in resource-constrained settings to perform sophisticated analyses (Fife, Brunwasser, & Merkle, 2023; R Core Team, 2023).

By continuing to evolve and adapt, SEM is well-positioned to remain at the forefront of statistical methodologies, driving innovation and supporting interdisciplinary research. Addressing its challenges while capitalizing on emerging opportunities ensures that SEM will continue to play a pivotal role in advancing scientific inquiry in the modern era.

Summary and Conclusion

Structural Equation Modeling (SEM) has come a long way (see more in Figure 2 and Table 2). What began as a blend of path analysis and factor analysis has grown into a powerful and flexible statistical framework used across fields like psychology, education, business, and health sciences. Thanks to key developments like Confirmatory Factor Analysis (CFA), Multi-Group SEM, Bayesian SEM, and Dynamic SEM, researchers now have the tools to tackle everything from validating complex measurement models to analyzing changes over time.

Still, SEM isn't without its hurdles. Challenges like messy or missing data, unclear model structures, and the need for large sample sizes continue to impact the accuracy of results. These issues remind us that, as useful as SEM is, it still needs refinement and thoughtful application. The good news? Cutting-edge technologies are opening new doors. Machine learning and big data tools are pushing SEM into exciting new territory, offering smarter ways to build models and uncover patterns in massive datasets. And with the rise of open-source tools—like the *lavaan* package in R—more researchers than ever can access and apply SEM, even in resource-limited environments.

In essence, SEM remains a foundational tool in the researcher's toolbox—not just because it's statistically powerful, but because it's adaptable. When used thoughtfully, it connects theoretical ideas with real-world data in a way that few other methods can. As we continue to face increasingly complex and interdisciplinary research questions, SEM's ability to evolve and incorporate new technologies ensures that it will stay relevant—and even become more essential.

Looking ahead, the future of SEM is bright. With ongoing innovations and broader access to user-friendly tools, researchers everywhere can harness their full potential. Whether analyzing social networks, healthcare outcomes, or market behavior, SEM is uniquely positioned to drive forward-thinking, impactful research in our rapidly changing world.

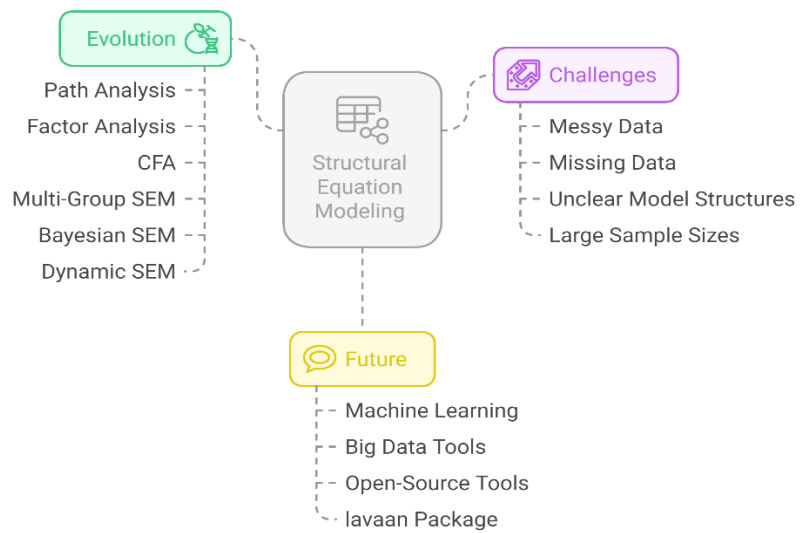


Figure 2 SEM: Evolution, Challenge, and Future

Table 2 Summary of Comparison of SEM Techniques

SEM Technique	Key Features	Strengths	Limitations
Confirmatory Factor Analysis (CFA)	Tests whether data fit a hypothesized measurement model.	High precision in validating latent constructs; useful for theory testing.	Requires a large sample size; sensitive to model misspecification.
Multi-Group SEM (MG-SEM)	Test model invariance across different populations or groups.	Useful for cross-cultural or demographic comparisons.	Complex model setup; requires strong measurement invariance assumptions.
Bayesian SEM	Incorporates prior knowledge into estimation via Bayesian inference.	Works well with small samples and complex models; full posterior distributions.	Requires prior specification; computationally intensive.
Dynamic SEM (DSEM)	Models changes in relationships over time (longitudinal SEM).	Captures time-lagged and feedback effects; ideal for temporal analysis.	Requires longitudinal data; can be computationally demanding.
Hybrid SEM + ML	Integrates SEM with machine learning (ML) algorithms.	Increases predictive power; suitable for high-dimensional data.	Interpretability challenges; risk of black-box modeling.

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