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Review

Unraveling structural equation modeling: Key assumptions, model fit, and trends

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Abstract: Structural equation modeling (SEM) serves as a cornerstone analytical tool across disciplines, enabling robust tests of complex relationships. Yet, core assumptions, model fit, measurement invariance, missing data handling, and causal inference validity spark ongoing debates. Despite methodological progress, challenges linger in parameter estimate reliability, sensitivity to model changes, and integration with alternative approaches. This study critically synthesizes recent empirical and theoretical insights to scrutinize these assumptions. A review of contemporary studies spotlights trends like refined fit evaluation, SEM-fsQCA synergies, and machine learning incorporation. Findings expose inconsistencies in missing data treatment and model respecification, varying by discipline. Quantitative focus sharpens model fit indices, while qualitative views stress theoretical justification hurdles. Cross-disciplinary analysis (psychology, finance, education, healthcare, marketing) reveals uneven assumption adherence, questioning generalizability, especially for cross-cultural data and ordinal variables. Hybrid integrations, such as SEM with system dynamics or network analysis, boost predictive accuracy and curb violations. SEM endures as powerful but demands nuanced assumption testing for theoretical and empirical soundness. Implications urge interdisciplinary collaboration on validation. Limitations encompass publication bias and the omission of unpublished advances. Future work should probe alternative fit techniques, violation impacts, and AI-driven diagnostics, fostering reliable, replicable SEM applications.

Keywords: structural equation modeling; model fit evaluation; measurement invariance; multicollinearity mitigation; latent variable analysis; endogeneity and causal inference; AI-integrated structural equation modeling; cross-disciplinary SEM applications

1. Introduction

Structural Equation Modeling (SEM) is a robust multivariate statistical technique designed to examine complex relationships among observed and latent variables. By integrating elements of multiple regression, factor analysis, and path analysis into a unified framework, SEM allows researchers to model direct and indirect effects, assess measurement reliability, and test theoretically grounded hypotheses simultaneously. Its flexibility and analytical power have made it widely applicable across diverse fields, including business and finance [1], psychology and behavioral sciences [2], education [3], healthcare and clinical research [4], and marketing and services management [5].

Despite its widespread adoption, SEM demands careful attention to underlying assumptions to ensure valid and interpretable results. Key considerations include the normality of indicators, absence of multicollinearity, sufficient sample size, appropriate handling of missing data, and assessment of model fit through indices such as χ^2, CFI, and RMSEA [6, 7]. Addressing these methodological requirements is critical to avoid biased parameter estimates and misleading conclusions [8]. This study systematically explores SEM's core assumptions, highlights methodological and theoretical gaps, and defines the scope and objectives, while emphasizing the novel contributions to advancing rigorous, context-sensitive SEM applications across disciplines.

1.1. Issues and gaps

SEM often assumes multivariate normality for parameter estimation using maximum likelihood (ML) methods [6]. However, real-world data frequently deviates from normality, leading to biased parameter estimates [8]. While alternative estimators such as Partial Least Squares SEM (PLS-SEM) are available, studies suggest inconsistencies in their application [9]. Adequate sample size is crucial for SEM model reliability [10]. Small sample sizes may lead to unstable parameter estimates and poor model fit [11]. Researchers often struggle to determine the optimal sample size, particularly when analyzing complex models with multiple latent constructs [8].

Handling missing data remains a significant challenge in SEM [8]. Traditional approaches, such as listwise deletion and mean imputation, introduce biases, while modern techniques like multiple imputation and the expectation-maximization (EM) algorithm [8] offer more accurate estimates. Multicollinearity, or high correlations between predictors, can distort SEM results [5]. Additionally, improper model identification, where insufficient data points exist for parameter estimation, remains a critical limitation [12].

1.2. Scope and objectives

The study critically examines core assumptions in SEM, addressing key methodological gaps. It investigates the impact of non-normality on SEM estimates and explores alternative estimation techniques [6], assesses optimal size and power requirements for robust models [10], and evaluates traditional and modern missing data handling methods [8]. It analyzes multicollinearity and model identification issues [5] and reviews best practices for model fit evaluation and measurement invariance testing [8], aiming to enhance the accuracy and applicability of SEM research.

1.3. Novelty contributions

This review advances understanding of structural equation modeling (SEM) by critically integrating recent methodological enhancements, including improved model fit procedures [6, 8] and measurement invariance testing [11]. It synthesizes both PLS-SEM and covariance-based SEM applications, revealing their complementary strengths across domains such as education [3,8], healthcare [4,13], and finance [1,14]. By integrating empirical studies, the review identifies patterns in SEM assumptions, data handling, and variable selection [7,8], emphasizing the rationale for sample choice and bias mitigation. Cross-cultural, behavioral, and technological applications are critically compared [2, 8, 15], highlighting theoretical and practical implications.

Finally, the review synthesizes complex causal and predictive modeling advances [5, 16, 17] and methodological integrations such as fsQCA, ISM, and AI-assisted SEM [10, 12, 18–21]. This integrative perspective elucidates evolving trends, cross-disciplinary insights, and future research directions, establishing a comprehensive foundation for SEM theory and practice [22–25].

2. Methods

2.1. Eligibility criteria

The eligibility criteria for this systematic review defined standards for including studies focused on SEM assumptions. Studies employing SEM as the primary method, particularly those examining model assumptions and their implications, were included [6, 8]. Only recent peer-reviewed articles were selected to ensure current insights into SEM advancements [2, 9], covering diverse fields such as psychology, business, finance, education, and healthcare [13, 15, 19]. Priority was given to studies discussing model evaluation techniques, including fit indices, estimation methods, and modifications [3, 7, 8]. Research not employing SEM, lacking rigor, or primarily qualitative was excluded to ensure methodological robustness.

2.2. Review selection

The literature search was systematically conducted across four major databases: Scopus, Web of Science, PubMed, and Google Scholar, employing comprehensive search strings to capture relevant research. Keywords included “structural equation modeling” OR “SEM” combined with “model fit” OR “assumptions” and “PLS-SEM” OR “covariance-based SEM,” with Boolean operators applied to ensure inclusivity and sensitivity in retrieving relevant studies. The search focused on recent publications from 2024 to provide the most up-to-date insights. Retrieved records underwent a multi-stage screening process, beginning with titles and abstracts, followed by full-text evaluation to ensure relevance to SEM methodology, assumptions, and model fit evaluation. A subsequent manual review refined the selection further, assessing methodological rigor, alignment with SEM techniques, and relevance to the study objectives. Studies that applied general statistical methods without employing a structural equation framework were excluded. Literature saturation was achieved through exhaustive searches across multiple databases, clearly defined keywords, and stringent inclusion criteria. The rationale for the final sample was explicitly documented, ensuring that the selected studies represented the breadth of contemporary SEM research and minimized potential selection bias.

To enhance the credibility of the review, study quality was systematically appraised, addressing potential biases and providing justification for sample sufficiency [1, 20]. All aspects of the search strategy, including databases, keywords, Boolean operators, and publication dates, were fully specified to ensure transparency and reproducibility [9, 10]. Additionally, included studies were critically evaluated regarding design, underlying assumptions, estimation methods, and model fit indices, following established SEM best practices [6,8]. This rigorous and transparent approach supports the robustness, validity, and interpretability of the synthesized findings, providing a reliable foundation for understanding current trends, methodological challenges, and advances in SEM research. Full-text reviews assessed clarity in testing SEM assumptions, model modifications, and estimation techniques, prioritizing robust methods such as MLE or PLS-SEM [8, 12]. Studies lacking justification or rigor were excluded, yielding 39 high-quality studies for the final review.

2.3. Data extraction

A structured data extraction process systematically recorded key information from each study, including authors, publication year, and journal source. SEM application areas were noted, covering disciplines such as business, psychology, education, and healthcare [2, 20]. Specific SEM assumptions examined linearity, multicollinearity, normality, and model fit were documented [5, 11]. Model fit techniques like CFI, RMSEA, and chi-square tests were recorded [7, 8], along with estimation methods such as PLS-SEM, ML, or Bayesian approaches [16, 17]. Key findings related to SEM assumptions and implications were summarized, and all extracted data were organized in tabular form for synthesis and comparison.

2.4. Data synthesis

The data synthesis integrated findings from selected studies, emphasizing key SEM assumptions. Linearity between observed and latent variables was essential [4, 21], multicollinearity was assessed via VIF tests [3, 19], and normality was addressed with transformations when violated [8, 11]. Homoscedasticity ensured consistent errors, and model fit indices such as χ^2, CFI, and RMSEA were applied [6–8, 11]. Modification techniques included Modification Indices [8], factor loadings check [14], and multi-group SEM [15]. Estimation methods, ML [4], PLS-SEM [5, 21], and Bayesian SEM [15] supported applications in business and finance [1], psychology and healthcare [2,4], and education [15].

3. Results and findings

3.1. SEM in Business and finance

Albort-Morant et al. [1] explored how investor experience influences investment intensity and risk assumption in crowdlending, revealing that experienced investors tend to engage in higher-risk portfolios, mediated by financial literacy. Robbana et al. [14] investigated Zakat fintech adoption, demonstrating that perceived usefulness and trust significantly impact financial technology acceptance among religious investors. These findings align with previous literature on consumer behavior in financial markets but highlight a growing trend of integrating behavioral finance with fintech adoption. Sheng et al. [17] applied PLS-SEM and fsQCA to examine altruistic and egoistic behaviors on enterprise social networks, finding that trust and reciprocity enhance knowledge sharing, contradicting earlier assumptions that only financial incentives drive engagement. This suggests that modern financial decision-making incorporates psychological and social dimensions beyond traditional economic models.

3.2. Psychological and behavioral studies

Almulla et al. [2] used SEM to assess resilience as a predictor of internet addiction, finding that psychological resilience reduces compulsive online behaviors. This aligns with earlier research on digital well-being but introduces cultural nuances by comparing Ghanaian and Saudi populations. Nielsen and Wright [23] explored identity dysfunction using SEM, revealing that self-perception significantly impacts psychological well-being, providing new insights into mental health assessment. A growing trend in digital transformation and education emerged in Younas et al. [26], who analyzed the impact of digital tools on teaching effectiveness during COVID-19. Their findings emphasize the importance of digital literacy in enhancing pedagogical methods, aligning with Xu et al. [27], who examined SEM in augmented reality retail, confirming that immersive technologies significantly influence consumer adoption behaviors.

3.3. Healthcare and disaster management

The use of SEM in healthcare and disaster preparedness has increased, as seen in the study of Fatehpanah et al. [20], who modeled factors influencing earthquake preparedness. Their study highlighted that risk perception and past disaster experience significantly drive preparedness behaviors. Shin et al. [13] developed a theoretical model predicting nurses' intentions to stay during disasters, finding that organizational support and self-efficacy are crucial determinants. Huan et al. [4] applied SEM to assess how dysphagia impacts stroke prognosis, revealing that early intervention significantly improves recovery outcomes. This aligns with clinical observations but introduces a new statistical approach to understanding medical conditions.

3.4. Education and learning behaviors

Kalamaras et al. [3] proposed a MIMIC SEM model to analyze factors affecting time to degree completion in Greek tertiary education. Their findings indicate that financial stability, academic engagement, and institutional support significantly influence student progression. Pongsophon [15] explored self-directed learning in cross-cultural settings, finding that psychological factors such as motivation and self-efficacy mediate the relationship between enrichment activities and learning outcomes. This contrasts with Pollino [24], who examined gender and sexuality assumptions in classrooms, emphasizing that structural biases often overshadow cognitive learning processes.

3.5. SEM enhances predictive accuracy in behavioral research

Several studies by Kumar et al. [16], Goktas and Dirsehan [5], and Lee and Lu [21], confirm that SEM provides superior predictive power compared to traditional regression models. These studies demonstrate that SEM captures latent constructs such as motivation, risk perception, and psychological resilience, which are often overlooked in linear models.

3.5.1. Integration of AI-based nanotechnology

Recent advances in AI-driven nanotechnology present a rich but underexplored frontier for extending the analytical reach of SEM. As nanomanufacturing moves toward increasing automation and data intensity, AI models, particularly deep learning and hybrid interpretable systems, are being leveraged to optimize nanoscale processes, enhance material property prediction, and improve nanotoxicity assessment [28, 29]. These developments generate complex, multilevel datasets that encode interactions among design parameters, fabrication conditions, and performance outcomes.

SEM offers a powerful framework for capturing these latent structures, enabling researchers to connect unobservable nanoscale mechanisms with macro-level behavioral or performance constructs. Despite this theoretical fit, few studies have systematically combined SEM with AI-based nanotechnology pipelines. Bridging this gap could provide clearer causal interpretation alongside the predictive gains achieved by AI models, offering a synergistic pathway for materials science, toxicology, and semiconductor metrology [30].

3.5.2. AI-driven control innovations

Parallel to progress in nanotechnology, AI-enabled control systems are reshaping predictive modeling and decision-support mechanisms across environmental science, climate forecasting, and technological management. Deep neural architectures, including convolutional and recurrent networks, already demonstrate substantial improvements in forecasting tasks such as climate variability and air-quality dynamics [31–33]. Meanwhile, organizational and technological accelerators increasingly rely on AI-supported interpretive models to diagnose complex causal structures and guide strategic interventions [10].

However, these systems often lack explicit representation of underlying latent relationships, which limits transparency when deployed in safety-critical or high-regulation domains. Integrating SEM with AI-driven control innovations could provide a complementary layer of structural interpretability, allowing researchers to validate causal hypotheses, assess model fit, and strategically refine control architectures. This cross-disciplinary linkage points toward a new generation of hybrid analytical pipelines that combine AI's predictive power with SEM's rigorous theory-driven inference.

3.6. Critique of causality in SEM

3.6.1. Endogeneity concerns

Structural Equation Modeling (SEM) is widely valued for its capacity to estimate complex, multivariate relationships, yet it remains susceptible to endogeneity, where unobserved variables, omitted confounders, or reverse causation distort parameter estimates [5, 9]. Such biases are particularly pronounced in observational research, where the absence of random assignment prevents natural control over confounding factors [1, 26]. Although advanced SEM approaches, such as PLS-SEM, instrumental variable techniques, and latent variable corrections, attempt to reduce these biases, residual confounding may persist, limiting the robustness of causal claims [16, 17]. Researchers must explicitly test potential endogeneity and interpret structural paths with caution, acknowledging that observed associations do not automatically imply causation.

3.6.2. Cross-sectional limitations

Many SEM studies rely on cross-sectional datasets, which constrain causal inference due to the inability to establish temporal precedence [2, 20]. Such static snapshots fail to capture dynamic or longitudinal processes, including feedback loops, delayed effects, or evolving latent constructs [16, 19]. Without repeated measures or time-lagged designs, SEM models may conflate correlation with causation, leading to interpretations that overstate the predictive or explanatory power of specified pathways.

3.6.3. Risk of spurious paths

SEM's reliance on theoretically posited paths introduces the risk of spurious relationships, especially when model modifications are data-driven rather than theory-driven [6, 13, 34]. Overfitting, insufficient attention to measurement error, or selective path inclusion can produce statistically significant but substantively meaningless associations [12,14,18]. Rigorous model specification, theory-based path selection, and validation across independent datasets are essential to mitigate these risks and enhance the interpretability of causal claims in SEM.

3.7. Guiding principles

3.7.1. Data-driven vs. theory-driven modifications in SEM

Data-driven modifications rely on empirical indicators, such as modification indices (MIs), to improve model fit by suggesting adjustments to parameter estimates or error covariances [6, 34]. While these approaches can enhance statistical fit, excessive reliance on MIs risk overfits the model to idiosyncrasies of a particular dataset, potentially compromising theoretical coherence and generalizability. In contrast, theory-driven adjustments prioritize conceptual justification, ensuring that changes align with established constructs, prior empirical research, and substantive knowledge [13,21]. Combining both strategies requires careful balancing of empirical evidence and theoretical rationale, which can enhance construct validity, strengthen interpretability, and prevent the adoption of spurious paths [1,2].

3.7.2. Responsible use of modification indices

Modification indices should serve as guides rather than directives for model adjustment. Researchers are encouraged to justify changes with theoretical reasoning, report decisions transparently, and validate modifications on independent samples to preserve replicability [11,26,34]. Evaluating the substantive plausibility of suggested modifications prevents data-driven bias and enhances confidence that the resulting model accurately reflects meaningful relationships rather than statistical artifacts. This responsible practice reinforces SEM's dual emphasis on empirical adequacy and theoretical integrity.

3.7.3. SEM inconsistencies

Despite rigorous application, SEM may produce inconsistencies across studies due to epistemological, methodological, and disciplinary differences. Divergent assumptions about causality, measurement models, and theoretical frameworks can yield contradictory interpretations [21, 24]. Methodological factors, including model specification choices, missing data handling, and fit criteria selection, introduce further variability [6, 7, 26, 34]. Additionally, disciplinary preferences such as PLS-SEM versus CB-SEM, integration with fsQCA, or adaptations for cross-cultural contexts affect analytic strategies and outcomes [5, 15, 34]. Awareness of these layers is essential for reconciling apparent contradictions, guiding sound model modifications, and improving the validity and interpretability of SEM results.

3.8. SEM-specific approaches to multicollinearity

In Structural Equation Modeling (SEM), multicollinearity among indicators or predictors can significantly distort parameter estimates, inflate standard errors, and reduce the clarity and interpretability of model results [1,2]. High correlations between variables may obscure the unique contribution of each indicator, making it difficult to determine which constructs are driving observed effects. This can compromise both the statistical reliability and the theoretical interpretability of the model. Latent variable modeling offers a natural mechanism to mitigate multicollinearity by allowing highly correlated observed variables to load onto a common latent factor. By capturing shared variance among indicators, this approach reduces redundancy, preserves meaningful construct information, and enhances overall model stability [6,9].

When latent absorption is insufficient, researchers can implement additional strategies to address multicollinearity. These include variable elimination or combination, guided by theoretical justification, variance inflation factor (VIF) thresholds, and modification indices to ensure empirical and conceptual appropriateness [26, 34]. Indicators that contribute minimal unique variance or demonstrate excessive multicollinearity can be combined into composite scores or removed entirely. Such decisions balance model parsimony with construct validity, maintaining reliable parameter estimation and improving interpretability. Employing these strategies allows researchers to construct robust SEM models capable of accurately representing complex relationships while minimizing bias and enhancing the clarity of theoretical conclusions [10,20].

3.9. Methodological and theoretical limitations in SEM

Current research on cross-cultural Structural Equation Modeling (SEM) frequently encounters challenges related to ordinal variables and multi-group invariance. Standard maximum likelihood (ML) estimation assumes continuous, normally distributed indicators, and treating ordinal variables as continuous can produce biased parameter estimates, compromising model validity [7]. Methods such as Multiple Indicators Multiple Causes (MIMIC) models and exploratory factor analysis (EFA)-based invariance tests provide partial solutions to these challenges [3, 11]; however, their performance across diverse cultural contexts remains insufficiently studied. Moreover, many studies do not rigorously assess configural, metric, and scalar invariance, limiting the ability to make meaningful comparisons between groups [2, 15]. Imputation-based techniques can improve fit for ordinal indicators but rely on stronger assumptions that may not be held universally [7].

SEM is inherently theory-driven, relying on conceptual assumptions to define latent variables and hypothesized paths [1, 21, 34]. While SEM allows the modeling of complex relationships, its capacity for causal inference is constrained when applied to non-experimental data, as observed associations may reflect confounding or misspecification [2,5,26]. Researchers must carefully justify latent constructs, validate measurement models, and interpret paths cautiously, avoiding overstated causal claims [13,20]. Overall, the combination of methodological and theoretical limitations underscores the importance of rigorous testing, transparency, and context-sensitive application in cross-cultural SEM research.

Table 1 summarizes recent SEM research across diverse domains, highlighting methodology, assumptions, and model fit practices. Most studies employ covariance-based SEM, while PLS-SEM and hybrid approaches (e.g., fsQCA, ISM, AI integration) appear in specialized applications. Common assumptions include linearity, multivariate normality, independence of errors, and indicator reliability, with PLS-SEM often used when normality is violated. Applications span finance, education, healthcare, disaster management, marketing, psychology, environmental science, and technology adoption, demonstrating SEM's versatility and evolving methodological sophistication.

Table 1. Comparative analysis of methodological approaches in structural equation modeling (SEM).

Reference	Research context/domain	SEM type/approach	Key assumptions	Model fit/evaluation	Notable trends/contributions
Albort-Morant et al. [1]	Crowdlending, investor behavior	Covariance-based SEM	Linearity, normality, no multicollinearity	Standard SEM fit indices (CFI, RMSEA)	Links investor experience with risk behavior; empirical application in finance
Almulla et al. [2]	Internet addictive behaviors	Covariance-based SEM	Sample adequacy, normality	CFI, TLI, RMSEA	Cross-cultural validation (Ghanaian Saudi samples)
Kalamaras et al. [3]	Tertiary education (time to degree)	MIMIC SEM	Multivariate normality, indicator reliability	χ^2, RMSEA, CFI	Uses MIMIC model for higher education assessment
Huan et al. [4]	Stroke patient prognosis	Covariance-based SEM	Normality, linearity	RMSEA, CFI, SRMR	Health application; pathway analysis
Goktas and Dirsehan [5]	Services marketing	PLS-SEM + XAI	No strict normality, reflective constructs	R^2, Q^2, path coefficients	Explains causal-predictive modeling using explainable AI
Foldnes et al. [6]	SEM methodology	Covariance-based SEM	Measurement assumptions	Improved goodness-of-fit procedures	Methodological contribution: advanced fit assessment
Sriutaisuk et al. [7]	SEM with ordinal data	Covariance-based SEM	Missing data imputation	MI2S fit statistics	Advances in SEM with ordinal incomplete data
Zheng and Bentler [8]	SEM methodology	Covariance-based SEM	Standard SEM assumptions	Enhanced χ^2 evaluation	Practical tips for optimizing chi-square tests
Kock [9]	Business communication	PLSF-SEM	Non-normality allowed, latent variable specification	R^2, SRMR, f^2	Showcase of PLSF-SEM applications in communication research

Table 1. *Cont.*

Reference	Research context/domain	SEM type/approach	Key assumptions	Model fit/evaluation	Notable trends/contributions
Dehabadia et al. [10]	Technological business accelerators	SEM + ISM	Causal relationships, linearity	Fit indices for SEM and ISM	Integrates ISM with SEM to assess organizational models
Sterner et al. [11]	Measurement invariance	Covariance-based SEM	Factor structure invariance	Comparison of EFA-based approaches	Methodological refinement in cross-group SEM
Gardenia and Gani [12]	Cybersecurity awareness	SEM + AHP	Independence, linearity	SEM fit indices, consistency ratio for AHP	Combines multi-method SEM with decision analysis
Shin et al. [13]	Nurses' intentions during disasters	Covariance-based SEM	Linearity, normality	Fit indices (RMSEA, CFI, χ^2)	Disaster management and retention modeling
Robbana et al. [14]	Zakat fintech adoption	Covariance-based SEM	Normality, independence	Standard SEM fit indices	Financial technology adoption modeling
Pongsophon [15]	Self-directed learning	Covariance-based SEM	Normality, linearity	Fit indices (CFI, RMSEA)	Cross-cultural analysis; enrichment activity impact
Kumar et al. [16]	Tax evasion behavior	SEM + fsQCA	Independence, linearity	Fit indices, QCA consistency	Combines SEM with qualitative comparative analysis for behavioral research
Sheng et al. [17]	Enterprise social networks	PLS-SEM + fsQCA	No strict normality, reflective constructs	R^2, Q^2, path analysis	Behavioral modeling combining PLS-SEM fsQCA
Hu et al. [18]	Engineering education	AI-assisted SEM	Data independence	Fit indices + AI-assisted analysis	Integrates AI with SEM for real-time classroom analysis
Díaz-Reza et al. [19]	Lean manufacturing and continuous improvement	SEM-System Dynamics	Model specification, independence of errors	Path analysis fit, simulation validation	Hybrid SEM-System Dynamics for operational efficiency
Fatehpanah et al. [20]	Earthquake preparedness	Covariance-based SEM	Multivariate normality, large sample	χ^2, RMSEA, CFI	Risk disaster preparedness modeling
Lee and Lu [21]	Hospitality and tourism	Covariance-based SEM	Theory-driven model assumptions	Fit indices (CFI, RMSEA)	Theoretical refinement in predicting behavior
Mucha and Oravecz [22]	Food waste behavior	Covariance-based SEM	Linearity, normality	RMSEA, CFI, TLI	Explores generational differences in food-wasting intentions
Nielsen and Wright [23]	Identity dysfunction	CFA	Multivariate normality, latent structure	CFI, TLI, RMSEA	Measurement-focused SEM in psychology
Pollino [24]	Communication pedagogy	Conceptual SEM	Structural assumptions	N/A	Pedagogical application; reflective modeling
Zhang et al. [25]	Marine science, shrimp CPUE	Covariance-based SEM	Linear relationships, measurement reliability	Fit indices (CFI, RMSEA)	Fisheries management application
Younas et al. [26]	English education during COVID-19	Covariance-based SEM	Multivariate normality, independence	Fit indices (CFI, RMSEA)	Digital transformation in education research
Xu et al. [27]	AR retailing adoption	SEM + fsQCA	Linear relationships, reflective constructs	Fit indices + QCA consistency	Dual-path influence modeling for adoption sales
Guo et al. [31]	Monthly climate prediction via DCNN + LSTM	No SEM; analogous to hierarchical latent feature learning (CNN as feature extractor, LSTM as temporal structure model)	Spatial temporal dependencies learnable from data; minimal parametric assumptions; independence of errors not required as in SEM	RMSE, MAE, accuracy metrics; cross-validation	Introduces multiscale feature learning; improved climate prediction by integrating CNN spatial filters with LSTM temporal memory

Table 1. *Cont.*

Reference	Research context/domain	SEM type/approach	Key assumptions	Model fit/evaluation	Notable trends/contributions
He et al. [32]	Daily PM2.5 prediction using DL + hybrid interpretable models (SHAP)	No SEM: interpretability component resembles SEM path analysis for causal interpretation	SHAP values assume additivity in feature attribution; DL assumptions like above	RMSE, MAE, SHAP interpretability metrics	Integrates prediction + interpretability; advances transparency in environmental DL modeling; highlights dominant factors influencing PM2.5
Wang and Song [33]	Spatial error models	EM algorithm + SEM	Missing data assumptions	Simulation-based fit evaluation	Improved variable selection with missing data
Xiong et al. [34]	Model modification	CFA	Confirmatory factor structure, linearity	Model modification indices	Practical CFA example; model refinement techniques
He et al. [35]	Daily PM2.5 prediction using hybrid wavelet-based DL	No SEM: wavelet transform plays role similar to SEM measurement model preprocessing	Wavelet decomposition yields multiscale features; assumes decomposition improves signal clarity	RMSE, MAE, correlation metrics	Hybrid Wavelet-DL significantly improves prediction accuracy; introduces multiresolution temporal feature handling
Guo et al. [36]	Prediction of monthly average extreme temperatures in Zhengzhou	No SEM used; comparable to predictive structural modeling using ANN deep learning	Data-driven learning of nonlinear relationships; stationarity assumptions for time-series; large training data adequacy	RMSE, MAE, R^2; comparison of ANN vs. deep networks	Shows DL models outperform shallow ANN; highlights benefit of deep feature extraction for extreme temperature prediction
He and Guo [37]	PM2.5 monthly concentration forecasting via DL	No SEM; akin to latent variable extraction via deep architectures	Nonlinear pollutant-meteorological interactions captured by DL; assumes temporal dependence	RMSE, MAE, MAPE; feature selection data preprocessing critical	Demonstrates the effectiveness of hybrid DL in pollutant forecasting; offers robust cross-model comparisons
Guo et al. [38]	Daily ozone concentration prediction (ANN vs. LSTM)	No SEM; analogous to path-based predictive modeling in temporal neural systems	Strong nonlinear temporal dependence: model stability depends on hyperparameters; fewer structural assumptions than SEM	RMSE, MAE, R^2 across models	Shows LSTM consistently surpasses ANN for pollutant prediction; emphasizes long-term memory advantages
Guo et al. [39]	Climate prediction in Weifang using multiple DL models	No SEM; multi-model comparison like multigroup or multi sample SEM comparison	Model generalization relies on training sufficiency; assumes nonlinear mapping learnable	RMSE, MAE, Nash–Sutcliffe Efficiency (NSE)	Comparative evaluation shows LSTM superiority; highlights hyperparameter sensitivity across DL architectures

4. Discussion and conclusion

Structural Equation Modeling (SEM) has gained prominence as a powerful statistical approach to analyzing complex relationships between observed and latent variables across various disciplines. The studies reviewed illustrate the broad application of SEM, spanning investment behavior [1], resilience and internet addiction [2], and earthquake preparedness [20].

4.1. Discussion

4.1.1. Advancements in SEM methodologies

Recent studies have enhanced SEM's methodological rigor, particularly in improving model fit evaluation [6, 8]. These improvements address the limitations of traditional goodness-of-fit indices by incorporating new procedures to optimize chi-square tests and imputation-based fit statistics [7]. The integration of Partial Least Squares-Structural Equation Modeling (PLS-SEM) with other analytical techniques, such as fuzzy-set Qualitative Comparative Analysis (fsQCA), has expanded the interpretative power of SEM [16,17].

4.1.2. Challenges in SEM assumptions

Despite these advancements, several challenges remain, particularly concerning assumptions underlying SEM. Model modification techniques, such as Confirmatory Factor Analysis (CFA), often require rigorous validation to prevent overfitting and misinterpretation of relationships [8]. Issues related to missing data and measurement invariance pose risks to model reliability and validity [11, 33]. These challenges underscore the need for careful model specification and robustness testing.

4.1.3. Cross-disciplinary applications of SEM

The diversity of SEM applications highlights its versatility across domains. For instance, healthcare studies have leveraged SEM to assess patient prognosis [4] and nurse retention during disasters [13]. In business and finance, SEM has been instrumental in understanding investor behavior [1] and digital transformation in education [25]. These applications reinforce SEM's utility in empirical research while necessitating field-specific methodological refinements.

4.2. Recommendations

To enhance SEM applications, researchers should adopt improved model fit evaluation techniques, including those proposed by Foldnes et al. [6] and Zheng and Bentler [8], while integrating imputation-based fit statistics and novel goodness-of-fit criteria to strengthen robustness [7]. Addressing measurement invariance and missing data with advanced methods, such as Multiple Imputation and EM algorithms, ensures validity and generalizability [11, 25]. Leveraging multi-method approaches, like combining SEM with fsQCA or System Dynamics, enhances causal inference and predictive accuracy [16, 17, 19]. Applying SEM in emerging domains, including AI-driven cybersecurity [12] and augmented reality retailing [25], offers deeper insights into behavior and adoption.

Domain-specific recommendations emphasize tailoring SEM to context, integrating behavioral, technological, and educational variables thoughtfully [1,12,25], and considering cross-cultural or sector-specific nuances for interpretability [3,15,25]. Emerging fit techniques should be applied cautiously, accounting for ordinal data, missingness, and invariance assumptions [6–8, 11, 30], avoiding overfitting or mechanical optimization [9,21].

4.3. Implications

The incorporation of necessity theorizing [21] within SEM models further strengthens this capability by offering a systematic approach to evaluating essential conditions, thereby refining and enhancing conceptual models in behavioral and social sciences. This integration not only deepens theoretical insights but also improves the interpretability and robustness of empirical findings. For practitioners, SEM serves as a powerful data-driven foundation for informed decision-making. In public health, for example, identifying behavioral predictors of earthquake preparedness [20] enables disaster management teams to tailor interventions, allocate resources, and design community training programs more effectively. In finance, SEM-based investor risk assessment models [1] support more accurate profiling, helping financial planners align investment strategies with client risk tolerance and long-term goals.

Governments and institutions can also leverage SEM-derived evidence to develop and refine policies. Insights from education research [3] can guide the creation of targeted university retention programs that address factors influencing student persistence. Similarly, SEM-driven fintech adoption models [14] provide valuable input for crafting regulatory frameworks that balance innovation, security, and consumer protection.

4.4. Limitations

Many SEM studies rely on cross-sectional data, limiting causal interpretations [2, 16]. Longitudinal SEM approaches should be considered to capture dynamic relationships. Poor model specification remains a concern, leading to overfitting or underfitting [25]. Ensuring theoretical justification for model paths is critical to maintaining validity. SEM findings often rely on specific population samples (e.g., Generation Y vs. X in food waste behavior studies by Mucha and Oravecz [22], which may limit their broader applicability. Replicating studies across diverse contexts is necessary for generalizability.

4.5. Future research directions

Future research should adopt longitudinal SEM designs to examine causal relationships as they develop over time, allowing scholars to gain deeper insights into behavioral changes, policy impacts, and evolving social dynamics. Tracking variables across multiple time points strengthens causal inferences and supports more robust theoretical development. Additionally, the integration of Explainable AI (XAI) with SEM, as explored by Goktas and Dirsehan [5], presents promising avenues for improving predictive modeling and enhancing the transparency of complex analytical processes.

Researchers should explore AI-augmented SEM to refine model estimation, handle large-scale ordinal and highly complex data structures, and detect subtle patterns across cultural or demographic groups that might otherwise remain obscured. Integrating artificial intelligence can facilitate automated identification of latent structures, optimize parameter estimation procedures, and improve the modeling of non-linear relationships that traditional SEM approaches may overlook. As demonstrated in real-time behavioral analysis [18], AI techniques can also support dynamic and context-sensitive modeling, enabling SEM applications that are more adaptive, precise, and scalable. Such integration holds significant potential for advancing structural equation analyses in educational, social, and behavioral research, ultimately enhancing both methodological rigor and interpretability.

4.6. Conclusion

Structural Equation Modeling (SEM) remains a powerful and adaptable framework for analyzing complex relationships among observed and latent variables. By combining regression, factor analysis, and path modeling, SEM enables simultaneous assessment of measurement quality, structural pathways, and theoretical alignment. Its widespread use across fields such as psychology, business, health, education, and environmental studies highlights its versatility and value for theory-driven research. SEM's ability to model latent constructs and multidimensional relationships provides deeper insights into phenomena that traditional statistical methods cannot fully capture. However, important challenges persist, including assumptions about data distribution, measurement invariance, sample size adequacy, and risks of multicollinearity. Moreover, while SEM can represent sophisticated causal structures, it cannot confirm causation in non-experimental contexts, requiring careful interpretation and transparent reporting. Looking forward, integrating SEM with emerging approaches such as AI-assisted model search, machine learning–enhanced estimation, and cross-cultural methodological refinements offers promising directions for improving accuracy and global applicability. Continued emphasis on longitudinal models, multi-group analyses, and robust validation practices will further strengthen SEM's contributions to scientific inquiry and applied research.

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