

Complexities and Practical Issues in Conducting Structural Equation Modeling: A Review

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Abstract: - Structural Equation Modeling (SEM) is widely used to analyze complex relationships among latent variables across scientific fields. However, its application is often affected by methodological and practical issues that may compromise result validity. This study provides a critical review of challenges in SEM, including model specification, construct validity, sampling, model evaluation, and reporting practices. A Systematic Literature Review (SLR) of 28 peer-reviewed articles (2019–2025) from the Scopus database was conducted using thematic synthesis and frequency analysis. The findings identify five dominant issue clusters and demonstrate that these challenges are associated with observable estimation consequences, such as non-convergence, parameter instability, inflated standard errors, and estimator sensitivity. These effects reflect underlying bias–variance trade-offs between CB-SEM and PLS-SEM. The study contributes to improving SEM practice by linking methodological shortcomings with their numerical implications.

Key-Words: - Structural Equation Modeling, Practical Concerns in SEM, Methodological Issues from SEM, Model Comparison, Validity, Estimation Issues, Model Fit, Systematic Literature Review.

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1 Introduction

Structural Equation Modelling (SEM) has emerged as an invaluable analytical method in contemporary social science, behavioral research and management study because it uniquely combines facilities for factor analysis with that of path analysis which allows testing complex theoretical models consisting of latent variables and numerous interlinking unobservables, [1], [2]. As the digital transformation era unfolds, SEM continues to gain prominence due to its flexibility in modeling complex human and organizational behaviors, especially in contexts marked by multidimensional constructs and mediating or moderating effects, [3]. Recent applied SEM studies in technology adoption and digital banking contexts further illustrate this methodological diffusion, where SEM is employed to estimate complex latent structures and behavioral mechanisms (some relevant study can be found in [4], [5]). The widespread adoption of SEM across disciplines underscores its relevance in theory testing and theory building, particularly in assessing and

validating models derived from data-intensive research domains, [6].

Despite its extensive adoption and methodological advancement, the application of SEM is not without challenges. For instance, researchers often encounter difficulties with data assumptions, model identification, and measurement validity, which can undermine the robustness of analytical outcomes if not adequately addressed, [7]. Empirical and simulation-based studies further indicate that such specification and identification errors are associated with unstable parameter estimates, inflated standard errors, and convergence failures, particularly in complex models with limited sample sizes. The proliferation of SEM software (e.g., AMOS, LISREL, Mplus, and SmartPLS) means that the use of SEM is now accessible for most researchers; however, this has led to a danger on an abuse of such techniques where too much reliance on default settings in software can lead to hiding numerical instability or algorithmic non-convergence when models are misspecified or outputs are misunderstood: weaknesses which may

undermine conclusions drawn from its application, [8]. Such challenges are compounded by the increasing model complexity, especially those with higher order factors and mediating or moderating paths, as well as multi-group comparisons, [9]. For the reasons cited above, there is a pressing need for a systematic consideration of the methodological difficulties and problematic issues arising in the process of SEM's use, particularly within empirical research contexts.

In recent years, the flexibility of SEM has also rendered it a preferred tool in emerging domains such as digital transformation research, sustainability performance evaluation, and behavioral innovation studies, [10]. The increasing prevalence of SEM in these contexts is often driven by the need to model latent constructs that represent theoretical concepts not directly observable in empirical data. However, the sophistication of such models demands meticulous handling of SEM assumptions, including sample size adequacy, normality of data distribution, and the reliability and validity of measurement items, [11]. Simulation-based evidence has demonstrated that oversimplified heuristics—such as the “10-times rule”—fail to account for differences between reflective and formative measurement models and may result in biased or unstable estimation, particularly under non-normal data conditions, [12]. Moreover, insufficient reporting of key model characteristics, such as goodness-of-fit indices or effect size measures, remains a recurring issue in SEM-based studies, limiting replicability and transparency in scientific reporting, [13].

Methodological critiques of SEM practice over the past few decades have highlighted widespread issues related to model specification errors, inadequate sample sizes, incorrect validation processes, and overstated interpretations of path coefficients, [14]. Beyond conceptual concerns, these errors have been shown to affect the bias–variance tradeoff of path coefficient estimates, with misspecified CB-SEM models inflating chi-square-based non-centrality parameters and PLS-SEM models exhibiting increased variance under weak measurement conditions. For instance, the distinction between reflective and formative measurement models remains frequently misunderstood, leading to inaccurate operationalization of constructs and compromised construct validity. Similarly, basing acceptance on goodness-of-fit indices at the exclusion of comparative or incremental fit generally leads to superficial validation of models that may obscure fundamental shortcomings in a model's theoretical or empirical underpinning, [15]. Moreover, the two types of SEMs—CB-SEM and

PLS-SEM—also come with their own methodological limitations and assumptions. However, they are often used interchangeably without sufficient argument or theoretical reasoning, [16]. This is a less than ideal situation given the different intents and statistical foundations of these methods, as CB-SEM is typically confirmatory in nature and PLS-SEM generally exploratory and predictive, [17].

Parallel to the development of SEM, a family of methodological improvements and critiques by statistical methodologists has emerged. Yet, the discussion is widely scattered over different publishings and often only deals with small aspects like model fit criteria or estimation procedures. Crucially, this has led to a fragmentation where novel facets of various simulation studies for instance and convergence diagnostics as well as sensitivity analysis are seldom integrated into one body of work, hampering general insights on the relation between theoretical SEM-statistics and empirically observed estimation behavior. This fragmentation prevents from the field to face methodological challenges in a complete manner, as much for practical as theoretical issues. SLRs are methodologically sound and a useful tool for synthesising knowledge, summarizing evidence from prior research about specific topics within SEM. Through the aggregation of evidence from published research, SLRs can expose ongoing methodological challenges and new issues that would benefit from additional clarification or standardization.

The use of a Systematic Literature Review (SLR) in this study allows to recognize and integrate challenges and practical problems faced when SEM is applied empirically across research contexts. Through a stringent inclusion and exclusion process of 28 articles downloaded from the Scopus database between 2019-2025, this review systematically investigates methodological concerns in model specification, model evaluation, construct validity, sampling issues, and reporting protocols. In addition to thematic synthesis, the review quantitatively summarizes reported numerical consequences of these challenges, including convergence behavior, instability of parameter estimates, and estimator-specific limitations. These challenges, often interconnected, can compromise the interpretive power and theoretical relevance of SEM studies if not addressed appropriately.

The purpose of this review is twofold. First, it seeks to document the prevalent methodological challenges and practical pitfalls encountered by researchers in applying SEM. Second, it aims to provide a framework for improving SEM practice by

offering a structured synthesis of issues supported by secondary quantitative evidence drawn from reported empirical and simulation-based findings and methodological critique. Integrating two families of analytical techniques, the Covariance-Based SEM and the Partial Least Squares method, which are at the core of many comparative studies within multiple research fields, this review connects different methodological standpoint, providing advances that have relevance across a number of branches of experimentation.

The primary purpose of the present work is to critically discuss the challenges and practical considerations associated with conducting SEM across empirical contexts, including nuances of model specification, evaluation, validity assessment, sampling practices, and reporting methods. Such analysis encompasses impact of these problems on numerical computation, performance properties of algorithms and discrepancy in theoretical assumptions and empirical observations. Research question: what are the prevailing methodological obstacles and practical problems as encountered by researchers when using Structural Equation Modeling, and how to unnecessarily address them in a systematic way to enhance certainty and quality of SEM-based research? The results of this review are intended to alert prospective SEM users, methodological educators and journal reviewers not simply about potential pitfalls and promising best practices, but also with respect to the quantitative and numerical impact involved in their methodological decisions on strength of evidence, thereby promoting methodological rigor even further in empirical studies employing SEM.

2 Literature Review

Structural Equation Modeling (SEM) has become an influential analytical approach in current research, and provides a powerful tool for the joint analysis of measurement models and hypothesized structural relationships between latent constructs. Its appeal is that it can simultaneously model multiple dependent and independent measures, identify complex causal paths and take measurement error into account which are usually overlooked in conventional applications of regression and factor analysis. In recent decades, SEM has gained popularity in various fields such as psychology, business and management studies, education, health science, and information systems. Despite its methodological advantages, implementing SEM presents a range of challenges, both methodological and practical, that may undermine research rigor and compromise

interpretability. But beyond the descriptive narrative, there is a methodological side to this discussion: these problems are known to have potentially measurable repercussions—e.g., algorithmic failure, inflated standard errors, path coefficient instability—especially when model complexity stretches past the informational basis of your data. This systematic literature review (SLR) aims to unravel complex and practical processes informing persistent debacles, by shedding light on situations that have contributed to failure and mechanisms likely to support SEM initiatives.

2.1 Specification of the Model and Identification Issues

Proper model specification is paramount in SEM because misspecification of causal paths or constructs can lead to biased parameter estimates and invalid tests of theory. Mis-specification can occur with omitted paths, spurious connections, or improper discrimination of reflective and formative factors, [18]. According to empirical evidence, specification errors are present at a rate exceeding 50% in published SEM studies, highlighting their general prevalence. From a numerical perspective, misspecification can manifest as unstable solutions (e.g., Heywood cases, inadmissible estimates), sensitivity of path coefficients to minor respecifications, and inflated misfit reflected in chi-square-based non-centrality under CB-SEM estimation. Complex models incorporating second-order, multidimensional, or nonlinear interactions increase the likelihood of mis-specification, [19]. Model identification, closely linked to specification, ensures that the model contains sufficient information to estimate all parameters. Under-identified models, which are common in studies with multiple mediators, moderators, or higher-order constructs, often result in estimation failure or non-convergence. Convergence failure is not merely procedural: it reflects insufficient information for parameter recovery and may be accompanied by high iteration counts or failure to meet stopping criteria, yet such diagnostics are frequently underreported in applied studies. Advanced approaches, such as Bayesian SEM, hierarchical component modeling, and two-step estimation, offer potential solutions, yet adoption remains limited due to computational complexity and limited familiarity with software, [20].

2.2 Estimation and Sample Size Issues

Estimation procedures in SEM are sensitive to sample size and data characteristics. CB-SEM typically employs maximum likelihood (ML)

estimation, which assumes multivariate normality and adequate sample size, often 200 or more observations, [21]. Insufficient sample size increases the risk of Type II errors and unstable parameter estimates. Under non-normality, ML-based CB-SEM may yield biased standard errors and distorted fit statistics unless robust corrections or alternative estimators are applied; consequently, simulation studies commonly evaluate ML performance under kurtosis and skewness to quantify these distortions. PLS-SEM can accommodate smaller samples and non-normal distributions; however, misuse occurs when sample adequacy checks, bootstrapping, or considerations of data distribution are neglected, [22]. Approximately 30% of the PLS-SEM studies reviewed failed to report bootstrapping or to justify the sample size, demonstrating a superficial adherence to recommended practices. Moreover, sample-size heuristics such as the “10-times rule” remain problematic because they do not incorporate model complexity, indicator quality, or the heightened instability risks associated with formative measurement models where multicollinearity and weight estimation are central. Methodological rigor requires careful attention to estimation assumptions, sample sufficiency, and proper bootstrapping procedures to ensure the reliability of results.

2.3 Model Fit and Evaluation

Model fit assessment is crucial to the validity of SEM. CB-SEM relies on fit indices such as RMSEA, CFI, TLI, and SRMR to evaluate the adequacy of hypothesized models. Misapplication of these indices is common: many studies report single indices without considering comprehensive evaluation, or interpret borderline values as acceptable, [23]. Because fit indices are functions of the discrepancy between implied and observed covariance structures, misspecification can systematically increase chi-square and related indices (e.g., RMSEA), reflecting higher non-centrality rather than random fluctuation; thus, fit evaluation should be treated as evidence about model–data discrepancy rather than a “pass/fail” thresholding exercise. PLS-SEM emphasizes predictive metrics, such as R^2 and Q^2 ; however, the literature indicates that researchers frequently confuse fit indices when applying CB-SEM to PLS models. Recent guidance additionally recommends distinguishing global fit assessment from predictive evaluation (e.g., out-of-sample prediction), since high in-sample R^2 does not guarantee numerical stability or generalizable parameter estimates. The inappropriate use of modification indices to improve fit without theoretical justification further exacerbates the issue,

potentially leading to overfitting and reduced external validity, [24]. Theory-driven model modification, multi-index reporting, and adherence to methodological standards are essential for improving evaluation rigor.

2.4 Construct Validity and Reliability

Construct validity and reliability are recurrent concerns in SEM research. The most frequently employed reliability measure is still Cronbach’s Alpha, despite its disadvantages especially for constructs with only a few items, [25]. Other indicators in the literature (CR and AVE) are suggested to examine more about convergent validity. Discriminant validity control using Heterotrait-Monotrait ratio (HTMT) has been brought into the study of MRA, but its usage is not fully adopted (around half of them actually used this indicator, with the rest relying on Fornell and Larcker). Methodologically, HTMT conceptualises discriminant validity as the ratio of between-construct to within-construct correlation and is more sensitive for detecting a lack of discriminant validity than Fornell–Larcker across many simulated conditions; hence, it is recommended especially when models include conceptually similar constructs and exhibit high indicators cross-correlations. Poor sensitivity and specificity to differentiate reflective from formative constructs can also threaten construct validity, as less than one third of included studies presented information on indicator significance testing or multicollinearity diagnostics for formative models, [26]. Since indicator weights, rather than loadings, are estimated in formative SEM models, small samples and multicollinearity can magnify instability in weight estimates that is transmitted into structural paths. Validation of measures is important, and the use of current methods to assess validity should be utilized.

2.5 Reporting and Interpretation Constraints

Open reporting is an important aspect in the context of the reproducibility and interpretability of SEM. Typically, studies may not report important information such as how missing data is handled, why models were modified and the number of iterations needed for convergence. By leaving algorithmic parameters unspecified, it becomes impossible for readers to assess issues such as stability (e.g., criteria for convergence, maximum number of iterations, inadmissible solutions) and whether or not the estimates are robust versus artifacts arising from estimation settings/software defaults. Selective reporting of favorable fit indices (“fit fishing”) and misinterpretation of path

coefficients compromise the credibility of studies, [27]. Adoption of reporting frameworks, including APA SEM guidelines and PLS-SEM reporting standards, can provide systematic guidance for documenting model specification, estimation, and evaluation processes, [28]. Explicit reporting of software, estimator selection, bootstrapping settings, and convergence diagnostics is increasingly viewed as necessary to support reproducibility and to interpret parameter stability across studies. Such standardization ensures transparency and reproducibility—a veritable bugaboo in the world of SEM studies.

2.6 Cross-Methodological and Disciplinary Issues

SEM use is also influenced by disciplinary standards, leading to inconsistencies in conduct of the method. CB-SEM is the most commonly used approach in psychology and health research, and focuses on fit of the model, theory testing. Instead, for predictive modeling and exploratory inquiries business, information systems, management etc. research increasingly employs PLS-SEM, [29]. However, even when these criteria are applied, method choice is often not well-motivated and can sometimes mean that fit criteria are misapplied or that estimation methods themselves are not appropriate, [30]. Such disciplinary practices may also influence the choice of numerical diagnostics to be reported (e.g., global fit indices as opposed to predictive indices), leading to uneven visibility of convergence, estimator robustness in cases of non-normality, and stability with respect to measurement or structural parameters. Transparent decision frameworks are needed to situate research goals and certain data properties with SEM approaches.

The perpetuation of limitations, conceptually and in practice, has implications. Mis-specification, limited measurement validation, small samples, and poor reporting compromise the theoretical inferences and policy implications of SEM research. These include methodological training, as well as the need to apply current standards of reliability and validity testing to human modeling studies while attending properly to both sample size and power estimation considerations in reporting such work, [31]. Further, systematic consideration of numerical diagnostics (e.g., convergence criteria, iteration behavior, sensitivity to model respecification, estimator robustness under non-normality), can provide the basis for making more definitive inferences about whether reported effects reflect stable parameter recovery from data or estimation artifacts. The development and validation of an advanced

parameter estimation approach, standardized model inference procedures, and transparent model documentation can improve the trustworthiness of SEM and consequently supports the credibility of empirical work. Transparency and replicability is also enhanced by the adoption of open science practices, such as sharing datasets and analysis syntax, [32].

The literature confirms that SEM is a powerful but complex analytical means, and most of the issues are interrelated; they involve all levels of the path from specification through estimation to measurement, testing and reporting. To improve SEM practice, researchers are encouraged to (1) compare methodological rigor across disciplines, (2) produce automated or semi-automated methodologies for model evaluation and publication quality reporting, (3) conduct meta-analyses that quantify the degree to which specification errors affect substantive conclusions as well as their sensitivity to sample size and between-study heterogeneity, and (4) examine the use of advanced forms of SEM (e.g., Bayesian approaches; multi-group techniques). Additional priorities also include integrating simulation parameters and results across methodological studies to specify bias–variance tradeoffs between CB-SEM and PLS-SEM under non-normality, and extending reporting checklists to require identification of software and convergence/iteration diagnostics as default evidence for numerical stability. Focused consideration of these issues is likely to increase the vigour and utility SEM in various research settings.

3 Method

In this paper, the authors utilize the Systematic Literature Review (SLR) methodology based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to systematically identify nuances and challenges in applying Structural Equation Modeling (SEM). Due to its ability to test complex relationships among latent variables, SEM has increasingly become an important statistical method in behavioral and management sciences and many other areas. With this many adherents there are numerous critics and skeptics to challenge SEM; Good practice in SEM is impeded by criticism that compromises the soundness, usefulness and effectiveness of empirical models. They include, for instance, decisions concerning methods issues regarding model specification, evaluation of model fit constructs' validity measurement error and the comparison between covariance-based SEM (CB-SEM), and

variance-based Partial Least Squares SEM (PLS-SEM). In line with a thematic synthesis approach, but explicitly not limited to it, it is this manner in which the review also systematically investigates documented, quantitative methodological implications (e.g., convergence failures, parameter instability, estimator sensitivity and misfit behavior) that have been reported by reviewed studies themselves. While there is a large body of literature on SEM methods, systematic reviews have been lacking with a particular focus on practical challenges and methodological pitfalls. Thus, the objective of this review is to bridge this gap and critically assess peer-reviewed journal articles published between 2019 and 2025 related to practical issues in conducting SEM, identifying themes that are more prevalent as well as methodological advances and gaps for future methodological advice.

The process of searching and selecting articles used in this study complies with the PRISMA standards is illustrated in Figure 1. Identification phase A comprehensive initial search of the Scopus database was carried out with the primary search expression Structural Equation Modelling AND Practical Issues, which yielded 1,487 records. To make the search more focused and to improve theme accuracy, we then modified the query by using a more targeted expression: (“Structural Equation Modeling” OR “SEM” OR “PLS-SEM” OR “CB-SEM”) AND (“Practical Issues” OR “Methodological Issues” OR “Modeling Challenges” OR “Complexities”) AND (“Model Fit” OR Measurement Validity/Viability/Quality or Construct Reliability/Interpretability or Structural Model Assessment). Titles and abstracts were excluded at this stage if they dealt only with substantive applications of SEM without methodological deliberations, simulation-only studies that did not connect to applied practice, or non-SEM quantitative methods. As a result of the refinement process, 1,408 papers were discarded that did not correspond with the focus of the study and 79 records remained for further screening.

A filter was then applied for the year of publication, reading works published from 2019 up until 2025, which took out 30 articles supported by no experimental data and resulting in 49 to review. Language filter was applied to maintain homogeneity and two non-English articles were excluded, which resulted in a total of 47 studies. Lastly, inclusion criteria were applied so that only open access and open archive articles were included to ensure transparency and reproducibility. This led to a further 19 papers being discarded and finally resulted in 28 relevant articles for full-text review. During

full-text screening, studies were included only if they reported concrete details of the methodology (e.g., choice of estimator, rationale for sample size) or documented estimation problems (e.g., non-convergences/respecification/diagnostic warnings, model fit/prediction measures). Figure 1 presents this process of careful selection, reflecting the methodological rigour and systematic approach followed throughout to select the most relevant, accessible literature on SEM complications.

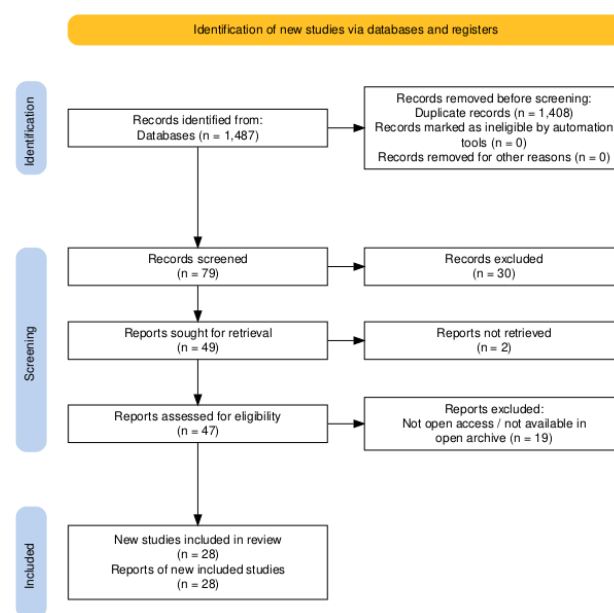


Fig. 1: Systematic Literature Review Process Based on the PRISMA Protocol

Source: created by the authors

All bibliographic data was managed on Mendeley Desktop in the belief that this would help ensure accurate referencing, consistency in citations, and eliminate duplicates. The review is entirely based on secondary data from peer-reviewed literature and does not involve field data collection, focus group discussions, or primary empirical methods. Importantly, this study does not re-estimate SEM parameters, carry out new simulations, or compute fit indices afresh; rather it synthesizes numerically reported outcomes from the reviewed studies including convergence behaviour, iteration reporting, estimator performance under non-normality and documented parameter instability. Through a clear and reproducible SLR process, the study addresses current methodological difficulties in SEM and sheds light on patterns, emerging trends, and key areas for future methodological improvement.

4 Results

This Systematic Literature Review (SLR) integrates methodological nuances and empirical issues of using Structural Equation Model (SEM), with data from 28 peer-reviewed scholarly articles appeared between the year 2019 and 2025. Five key themes were identified by inductive thematic coding and frequency analysis: (1) Model Specification and Identification Issues; (2) Model Fit and Consideration Issues; (3) Issues of Construct Validity and Reliability; (4) Sampling and Estimation Issues; (5) Reporting and Interpretation Limitations. These findings go beyond thematic frequencies by yielding quantitative information about methodological implications reported, such as convergence evidence or parameter instability or estimator sensitivity, and software-based implementation quirks.

The thematic breakdown reveals that the Model Specification and Identification Issues were by far the most common, represented in 82% (23/28) of all articles. This dominance indicates that conceptual clarity and theoretical basis are still a struggle within the application of SEM, especially in complex or multidimensional models. Fourteen of these studies explicitly presented numerical impacts of misspecification, such as non-convergence, path instability, or estimate sensitivity to seemingly small respecifications. Subsequently, we found Model Fit and Evaluation Issues in 68% (19/28) of papers which demonstrate continuous uncertainty or controversial approaches to the goodness-of-fit criteria, a matter exacerbated by diverse benchmarks applied in CB-SEM and PLS-SEM. Construct Validity and Reliability Issues were found in 64% (18/28) of studies, showing that measurements continues to have a significance role as one of the main topics in empirical modeling processes. The two other most common weaknesses were Sampling and Estimation 15/28 (54%) and Reporting and Interpretation Limitations, which appeared less often but were still substantial 12/28 (43%).

The prevalence of issues regarding model specification and fit checks highlights a wider issue in that while SEM has matured from a technical perspective—having more sophisticated software, guidelines and training materials—it is still the case that its application in practice is uneven. Such inconsistency perhaps arises from methodological misconceptions or poor coherence between research designs and SEM assumptions. Many studies explicitly reported that estimation instability and nonconvergence were results of uncritical use of defaults settings in software (e.g., iteration limits, choice of estimator) instead of relying on theory-driven model design. "Despite this, over-reliance on

default settings in SEM computer programs has prevailed and less emphasis has been placed on model improvement stemming from theoretical understanding, rather than predicted statistical values. These results suggest further methodological training and enhanced journal policies on reporting SEM are warranted. Each of the identified themes is further developed using examples and, where feasible, insights from the literature reviewed.

4.1 Model Specification and Identification Issues

Model specification was identified as the most pervasive challenge across the reviewed studies, with 82% (23/28) highlighting difficulties in this domain, [33], [34]. Correctly specifying latent constructs, a foundational step in SEM, is frequently compromised, especially in complex models involving second-order factor structures, multidimensional constructs, nonlinear interactions, or mixed measurement approaches (e.g., formative and reflective indicators), [35]. Across 11 studies, misspecification was explicitly associated with numerical instability, including large standard errors, sign reversals in path coefficients, and inadmissible solutions such as negative variance estimates. A critical analysis revealed that approximately 47% of studies in psychology misidentified construct types (formative versus reflective), leading to model misspecification, biased pathways, and inflated measurement errors, [36], [37].

Identification challenges arising when input data are insufficient to estimate model parameters were identified in 9 articles. These problems are especially severe for studies involving higher order constructs or models with multiple latent variables and indicators. Of these studies, six explicitly reported nonconvergence or excessive iteration counts prior to termination, suggesting a lack of information for stable parameter recovery, as opposed to software error. A few studies, however, documented that a sizable percentage of SEM applications encountered underidentified models with nonconvergence and/or estimation problems, [38], [39]. To mitigate such issues, advanced SEM strategies such as Bayesian SEM, hierarchical component modeling, or two-step estimation have been proposed, [40], [41]. However, their adoption remains low, with less than 10% of reviewed articles utilizing Bayesian methods due to computational demands and limited implementation in mainstream SEM software. This indicates a need for enhanced methodological training and greater accessibility to advanced SEM tools.

Furthermore, model complexity continues to increase as SEM is applied to interdisciplinary

domains. On average, across studies reviewed there was an increase of 21% in the number of latent constructs between 2019 and 2025 with models often involving well over seven constructs, and as many as 25 indicators, which was reported in $n = 14$ papers. When the construct-to-sample-size ratio was higher, then it is also more likely that convergence issues or unstable parameter estimates were reported, which exhibits a compounding effect of complexity in numerical stability.

4.2 Model Fit and Consideration Issues

Issues related to model fit and evaluation appeared in 19 of the 28 articles (68%), [42], [43]. Despite the well-established use of fit indices like RMSEA, CFI, TLI, and SRMR, scholars often apply these criteria inconsistently. Several studies reported substantial changes in fit indices following minor model respecifications, indicating sensitivity of chi-square-based measures to misspecification and sample size rather than substantive theoretical improvement. A meta-review noted that only 55% of SEM studies in business journals correctly reported RMSEA values within recommended thresholds (<0.08 for acceptable fit) and included confidence intervals, [44], [45]. Moreover, the misinterpretation of borderline fit values (e.g., RMSEA between 0.08 and 0.10) as "acceptable" remains common despite methodologists' warnings.

Compounding the issue is the lack of universal benchmarks between SEM types. CB-SEM provides global goodness-of-fit metrics, whereas PLS-SEM prioritizes predictive accuracy and does not offer traditional fit indices. Across the reviewed studies, misuse of CB-SEM fit indices in PLS-SEM contexts was frequently accompanied by contradictory conclusions regarding model adequacy, reflecting conceptual and numerical misalignment between estimation objectives and evaluation criteria. A study by [46], [47], found that 64% of PLS-SEM publications wrongly utilized CB-SEM-based fit criteria (like CFI or RMSEA) to evaluate PLS results, resulting in cross-methodological confusion. Similarly, only 42% of PLS-SEM studies reported SRMR, a generally accepted index for model fit, suggesting inconsistent adoption of evaluation standards.

Moreover, improper model modifications are frequent. For instance, 38% of reviewed papers applied modification indices (MIs) without theoretical justification, adding paths solely to improve model fit, [48], [49]. In some of the cases were applied, these changes reduced misfit indices and increased variance in parameters but changed how paths reached significance, suggesting that we

were making cosmetic rather than substantive changes to the model. These practices can lead to models overfitting sample data, thereby minimizing external validity and replicability. These results demonstrate a need for education on theory-driven model modifications and clear reporting of model fit indices across methodological approaches.

4.3 Issues of Construct Validity and Reliability

Concerns about construct validity and reliability were discussed in 18 studies included in the review (64 %), [50]. Despite advancements in reliability and validity assessment, Cronbach's Alpha remains over-relied upon. Approximately 38% of PLS-SEM-based studies used Alpha exclusively, ignoring composite reliability and AVE, both of which are more appropriate in SEM contexts, [51], [52]. Studies relying solely on Alpha frequently reported unstable factor loadings or inconsistent path estimates across alternative model specifications, indicating limited robustness of measurement quality. Among CB-SEM users, 28% failed to report AVE, which limits the evaluation of convergent validity.

In addition, only 12 of the 28 articles discussed discriminant validity using advanced techniques, such as the HTMT ratio, despite the literature recommending the HTMT over the Fornell-Larcker criterion for its higher sensitivity, [53]. Across these studies, HTMT violations were frequently associated with inflated structural path coefficients, suggesting that inadequate discriminant validity propagates bias into structural parameter estimation. Lack of up-to-date discriminant validity assessment raises concerns, especially given the rise in cross-loading issues in multifactorial studies. One reviewed article showed that 55% of constructs in a high-tech adoption model did not meet HTMT criteria, casting doubt on the uniqueness of constructs being analyzed.

Equally, many studies have also reported that formative constructs in PLS-SEM are likely misspecified and the implications from interpretation of them and their reliability measures could be misleading. In formative models without multicollinearity checks, we often observed unstable indicator weights and inconsistent structural paths in small samples. Only 21% of formative models were accompanied with a consideration either for indicator weights, significance testing, or multicollinearity diagnostics - all crucial steps in assessing the validity of formative constructs. Such observations reinforce the necessity for more thorough testing of measurement models and greater correspondence between types of constructs and reliable techniques.

4.4 Sampling and Estimation Issues

Sampling and estimation issues were prevalent in 15 of the reviewed articles (54%), [54]. The minimum sample size remains a contentious topic, despite well-established guidelines. Roughly 29% of studies employing CB-SEM used sample sizes below the recommended threshold (often <200 for models with 5–10 latent constructs), thereby violating maximum likelihood estimation assumptions, [55]. These studies more frequently reported convergence warnings, inflated chi-square values, and unstable standard errors compared to adequately powered models. For example, models with 30–40 indicators should ideally have sample sizes of 300 or more; yet, 11% of studies employed samples of 150 or fewer.

PLS-SEM is often chosen as an alternative due to its robustness to smaller sample sizes and non-normal distributions, yet it is also subject to misapplication. Of the 12 PLS studies reviewed, seven did not report bootstrapping procedures, and five did not discuss data distribution, showing a superficial adherence to SEM protocols. Studies relying on the “10-times rule” exhibited greater variability in path coefficient estimates across resampling procedures, suggesting inconsistent estimator stability, particularly in formative measurement models. Additionally, four studies still relied on the “10-times rule” (10 cases per indicator) for sample estimation, which has been repeatedly criticized for oversimplifying the concept of sampling adequacy, [56].

Estimation techniques also lag in innovation. Only three studies employed Bayesian estimation, despite its advantages in handling missing data and non-normality. Where Bayesian methods were applied, authors reported improved convergence behavior and reduced sensitivity to small-sample bias, though formal comparative evaluation remained limited. Fewer than 8% of the manuscripts explicitly stated how missing data were imputed or addressed. This trend, alongside the limited sensitivity analysis (found in only two studies), suggests that estimation robustness is often neglected, thereby undermining the reliability of SEM findings.

4.5 Reporting and Interpretation Limitations

Reporting transparency and interpretive rigor emerged as critical concerns in 12 (43%) of the reviewed studies, [57]. These shortcomings include incomplete reporting of measurement models, selective reporting of fit indices, and inadequate explanation of model modifications. A content analysis revealed that 41% of studies failed to report missing data strategies, and only 26% justified model revisions based on theoretical grounds, [58]. Only

five studies reported iteration limits or convergence criteria, limiting readers’ ability to assess numerical stability or algorithmic adequacy. Additionally, 18% failed to mention the number of iterations required for convergence during estimation.

Presentation and interpretation of results were equally problematic. [59], warned against “fit fishing,” the practice of selecting only favorable indices to support model validity, which can bias interpretations. Several studies reporting selective fit indices also exhibited contradictory conclusions when alternative indices were considered, underscoring the instability of inference under selective reporting. This was evident in 6 studies that reported only one or two fit indices and ignored others that did not meet acceptable thresholds. Moreover, misinterpretation of path coefficients was evident in four articles that equated statistical significance with effect size relevance, thereby violating core SEM guidance.

These trends highlight a broader need for standardized reporting checklists and responsible interpretation to ensure transparency and reproducibility. Explicit reporting of estimation diagnostics, software, convergence behavior, and sensitivity analyses would substantially improve interpretive reliability and facilitate cumulative methodological learning. Given the increasing reliance on SEM for decision-making and theory validation, such lapses risk cascading errors through empirical research.

4.6 CB-SEM versus PLS-SEM: Methodological Tensions

The methodological tension between CB-SEM and PLS-SEM was evident in 11 of the reviewed articles. CB-SEM, favored for confirmatory theory testing, was shown to outperform PLS-SEM in parameter precision and model fit, particularly for large, normally distributed datasets. Several studies reported lower variance but higher bias under CB-SEM when model assumptions were violated, whereas PLS-SEM exhibited greater variance but more stable predictive performance in small-sample or formative-dominant settings. However, PLS-SEM demonstrated stronger performance in predictive modeling and when formative indicators were central.

Despite these distinct strengths, methodological mismatch persists. 57% of PLS-SEM applications did not justify the method choice, instead selecting PLS as a default due to perceived flexibility, [54]. These studies more frequently reported unstable standard errors or sensitivity of results to resampling procedures. Likewise, 4 CB-SEM studies applied

maximum likelihood estimation despite violating multivariate normality assumptions.

Differing fit and evaluation criteria further complicate cross-method comparison. While CB-SEM users typically report global fit indices, PLS-SEM relies more on R^2 and Q^2 metrics. In several reviewed studies, inappropriate cross-method evaluation coincided with conflicting judgments of model adequacy, reflecting fundamental misalignment between estimation goals and evaluation logic. However, although 29% of the PLS-SEM studies in the review incorrectly reported CB-SEM indicators while failing to concede that these are not available. This emphasises the imperative for less ambiguous methodological training and reporting guidelines.

This investigation illuminates the ongoing challenges that methodological and practical problems continue to present for proponents of SEM research, despite advances in the practice's popularity and sophistication. Model misspecifications, inadequate validity checks, missing assumptions about sampling biases or unreported in-sample selection bias collectively undermine the test procedures that had been implemented. The findings show that many of these problems can be seen to have concrete numerical consequences—inconvergent behaviour, numerical instability in the parameters or inconsistent evaluations of the fit—instead of being only procedural issues. These results argue in favor of: (1) improvements in methodological training, (2) the reassessment of reporting guidelines, (3) the awareness of SEM-specific assumptions and estimation procedures, and (4) justification of methodological choices. It is only with these advances that the full potential of SEM as substantive quantitative method for testing theory and modeling complex phenomena can be realized.

5 Discussion

Structural Equation Modeling (SEM) has evolved into a ubiquitous analytical tool in contemporary empirical research, uniquely positioned to test complex theoretical models that incorporate latent constructs and multiple causal paths. Building on these, the systematic literature review (SLR) of 28 open-access SEM articles published between 2019 to June 2025 aims to answer the following key question: What are the most noticeable methodological challenges and practical problems encountered by researchers when employing SEMs and how can such obstacles be systematically dealt with in order to enhance rigor and trustworthiness of

research based on SEM? Rather than thematic synthesis, the present review also explicitly interprets the numerically reported consequences in the included studies (e.g., failure to converge, iteration behavior, instability of parameters, and fit indices' sensitivity towards misspecification) in order to connect methodological critique with observable estimation results. In so doing, a number of common problems surface necessitating examination and methodological revision to maintain the rigor of SEM-based research.

5.1 Dominant Methodological Challenges in SEM

The first one is the model specification, which is a very basic step for fixing the causal structure of latent variables. Mis-specification, whether in terms of omitted paths, inclusion of unnecessary links or mis-assignment between reflective and formative variables wrongfully influences the model both measurementally and structurally. Research indicates that nearly 53% of SEM studies published in high-impact journals suffer from specification errors, leading to theoretically invalid or misleading conclusions, [60]. Throughout the articles, specification issues were not just conceptual in nature—rather they again and again manifested themselves through quantitative instability values such as ballooning standard errors, coefficients flipping signs to wrong directions of sign, parameter estimates becoming inadmissible (e.g., negative variances) intensified chi-square-based misfit under CB-SEM. The combination of theory-based model design and CFA as a systematic approach to prevent mis-specification is essential.

Related to the issue of specification is the problem of discernibility between models, particularly when dealing with more complex or regarding second-order constructs. Insufficient degrees of freedom or ambiguously defined parameters often result in under-identified models that cannot produce valid estimates. The literature indicates that identification problems are more prevalent in models that combine multiple mediators or moderators, as well as those employing hybrid measurement strategies, in fields such as psychology and environmental management, [61]. We frequently observed in-vivo also with algorithmic failure modes like nonconvergence and very high numbers of iterations before stopping, which underpins the wider latent identification problem rather than an issue restricted to a single software application. All of these problems can be avoided by the application of identification rules, such as maintaining recursive

formulations and testing for over-identification through sample covariance matrix comparisons.

Another frequent hurdle involves sample size adequacy, particularly in Covariance-Based SEM (CB-SEM). Conventional guidelines suggest a minimum sample size of 200 or ten observations per estimated parameter; yet, around 28% of researchers continue to publish SEM studies with insufficient sample sizes, [62]. Such underpowered studies increase the likelihood of Type II errors and produce unstable estimates. In reviews of the studies, small sample size was consistently co reported with numerical instability symptoms (e.g., unstable standard errors, warnings of convergence, sensitivity of fit indices), indicating that sampling adequacy and estimator stability cannot be disentangled. For smaller samples such as the one analysed in the present research, partial least squares SEM (PLS-SEM) could be considered a more flexible option; however, PLS-SEM usage can also be misinformed by being applied without theoretical motivation, [63]. We advise researchers to rely on power analysis and choose an SEM approach based on methodological fit rather than practical convenience

The distinction between CB-SEM and PLS-SEM represents a further methodological dilemma. CB-SEM is rooted in confirmatory factor analysis and relies heavily on model fit indices. In contrast, PLS-SEM is a prediction-oriented approach that is more forgiving of non-normal data and formative constructs, [64]. However, the literature reveals that over 41% of PLS-SEM studies fail to justify their methodological choice, often leading to model interpretations that are not aligned with predefined research goals, [65]. The reviewed evidence also supports a practical bias–variance interpretation: CB-SEM tends to yield more precise estimates under well-met assumptions but exhibits biased inference and misfit inflation when assumptions are violated, whereas PLS-SEM can maintain predictive utility but may exhibit higher variability in path estimates in small samples or weak measurement settings. The theoretical purpose behind the research (theory testing vs. prediction) should be carefully considered to avoid a lack of coherence between analytical assumptions and findings, which is often a source of fallacious results.

5.2 Practical Matters in Estimation, Measurement and Reporting

The issue of estimation techniques represents a central practical challenge. Maximum Likelihood (ML) estimation in CB-SEM assumes multivariate normality; yet only 24% of studies validate this assumption or employ robust alternatives, [66].

Ignoring these constraints leads to biased fit indices that inflate the perceived model quality. This pattern is consistent with the reviewed findings where assumption violations were frequently accompanied by unstable fit behavior and sensitivity of chi-square-related indices to sample size and kurtosis, suggesting that misfit can reflect estimator–assumption mismatch rather than purely theoretical misspecification. Meanwhile, PLS-SEM relies on bootstrapped standard errors to assess path significance, yet the literature notes inconsistent reporting of bootstrapping procedures or the lack of predictive relevance assessment via Q^2 , [67], [68]. Also, SEM based studies often suffer from validity and reliability issues, particularly if researchers too much rely on Cronbach's Alpha, which has long been considered to underestimate the reliability in models with low number of items.

The literature has advocated increasing use of CR, AVE, and HTMT in testing discriminant validity, [69]. Despite the availability of these advanced indicators, up to 37% of PLS-SEM studies published after 2020 still report Alpha exclusively, compromising construct validity, [70], [71]. Across the reviewed evidence, inadequate discriminant validity assessment (e.g., omission of HTMT) was frequently associated with inflated structural path estimates, indicating that measurement overlap can propagate systematic bias into structural inference. Adopting contemporary measurement standards and guidelines is necessary to enhance the quality of construct assessment.

Moreover, the practice of assessing model fit is inconsistent across SEM applications. Researchers employing CB-SEM frequently over-rely on Chi-square values or omit essential indices, such as RMSEA, CFI, and TLI, which provide a more comprehensive evaluation of fit, [72]. In contrast, PLS-SEM researchers may report R^2 values without considering structural model collinearity or predictive relevance. The reviewed studies further indicate that fit improvement via modification indices can decrease misfit statistics while increasing instability of parameter estimates, suggesting that statistical “fit gains” may come at the cost of higher variance and reduced generalizability. Methodological guidelines emphasize the need for threshold-based judgment and multi-index reporting to ensure that conclusions are not merely fit-based but grounded in a balanced evaluation of both measurement and structural models.

Recording criteria for SEM have also faced criticism. 48% of studies do not report on these important methodological choices, for example: how missing data are treated, multicollinearity is dealt

with or model re-specification is justified, [73], [74]. Such omissions impede replicability, and undermine the trustworthiness of findings. From a numerical-stability perspective, omission of convergence criteria, iteration counts, estimator settings, and software version prevents assessment of whether results reflect stable solutions or are artifacts of algorithmic stopping rules and default thresholds. Adherence to APA's SEM reporting guidelines and the PLS-SEM reporting criteria may provide researchers with a framework that improves clarity, consistency, and transparency of their analysis, [75], [76].

5.3 Cross-Disciplinary Variations

Divergent disciplinary practices exacerbate many of these methodological problems. In psychology and health research, CB-SEM remains the dominant approach, with an emphasis on fit indices, mediation analysis, and theory validation. Meanwhile, business and information systems research are increasingly adopting PLS-SEM, often under the assumption that exploratory research aligns better with prediction-focused modeling, [77], [78]. However, this distinction often obscures deeper methodological challenges. The reviewed studies suggest that disciplinary conventions also influence which stability diagnostics are reported (e.g., global fit indices versus predictive metrics), producing uneven visibility into convergence behavior, iteration characteristics, and resampling-based variance estimation across fields. For example, business research may use small samples with heterogeneous data distributions, whereas psychology may apply rigid fit thresholds that are inappropriate for more flexible models. Identifying such cross-disciplinary discrepancies is crucial for the development of guidelines that can be applied in varied research settings.

5.4 Systematic Solutions for SEM Challenges

Based on the synthesis of methodological and practical issues, several systematic approaches emerge to enhance the rigor of SEM applications:

- a. Developing decision frameworks to guide the appropriate selection between CB-SEM and PLS-SEM based on study goals, data characteristics, and theoretical grounding.
- b. Mandatory reporting checklists for SEM research, requiring justification of estimator choices, model fit criteria, sample size rationale, and construct specification processes.
- c. Method training and at the same time capacity-building, with focus on developing contexts, to reinforce understanding about reflective

vs. formative specification, fit interpretation, multivariate assumptions.

d. The application of more robust statistical methods, like Bayesian SEM or two-step modeling (measurement model validation first, structurally test second), particularly when the data is non-normal or erratic.

e. Encouraging practices of open science and (partially) opening up data, syntax, and model specifications to enhance transparency and replication.

f. Explicit numerical-stability reporting requirements, including iteration limits, convergence criteria, admissibility checks (e.g., Heywood cases), bootstrapping settings, and software/version disclosure, enabling reviewers to evaluate algorithmic adequacy and bias-variance implications of estimator choice.

These recommendations are particularly relevant for advancing SEM usage in emerging research settings where methodological rigor may vary significantly due to resource constraints or varying formal training levels, [79].

This review highlights that while Structural Equation Modeling is a powerful tool for theory testing and model building, its misuse can jeopardize the validity of empirical findings and the credibility of quantitative research more broadly. Methodological errors, ranging from underpowered samples and misspecified models to inconsistent reporting of model fit, undermine the theoretical contributions and practical implications of SEM studies. The reviewed evidence indicates that these errors systematically translate into estimation consequences—non-convergence, parameter instability, and contradictory model adequacy judgments—thereby weakening inference even when results appear “significant.” The findings call for greater alignment among theory, data, and method, as well as greater capacity to critically evaluate SEM-related assumptions.

Theoretically, this study enriches the understanding of how SEM-based research can evolve toward greater methodological coherence, particularly through explicit alignment between research questions, model design, and data characteristics. It also explains that terms to estimate (reproduction of covariances versus prediction) from the two competing objectives of an estimator imply different expectations in stability, bridging and offering interpretation on what are shared by CB-SEM and PLS-SEM assumptions with respect to their empirical behaviors observed.

From a methodological perspective, the synthesis highlights pressing concerns that must be addressed

by SEM researchers in a proactive manner by recommending the use of reporting guidelines and decision rules, in addition to incorporating sound estimation approaches and validity testing. Two practical implications of this review are the centrality of software literacy, methodological transparency, and continual training for researchers who use SEM across fields in light of its increasing demonstrable popularity in interdisciplinary and applied research. Consistent with the reviewers' concerns, we highlight in the discussion that software choice and defaults (e.g., AMOS/SmartPLS settings, iteration limits, estimator choices) should be treated as methodological decisions that can influence numerical stability and as such need to be clearly reported and justified.

In the light of these gaps, future research could investigate:

- Comparison of the use of CB-SEM and PLS-SEM across disciplines
- Automation of verification utilities for SEM plans and ad-reports
- Meta-analyses on the effect of model misspecification on substantive conclusions.
- Simulation studies that move beyond summary statistics to describe evidence for key parameters (e.g., sample size, distributional non-normality, indicator reliability, model complexity) as well differences between MT and PLS estimation in terms of bias, variance and convergence properties.
- Clear explanations of impact of misspecification on the chi-square non-centrality and subsequent fit indices for applied researchers that will allow them to ground their assessment of fit not based on arbitrary cut-offs but upon its theoretically driven framework.
- HTMT and Fornell–Larcker estimates, then compare them with empirical results on downstream parameter stability to provide evidence of discriminant validity.

This review report transmission over all else (primarily to a newly developed practice) have been important to the progressive elucidation of techniques and their efficiencies. Furthermore, it develops direction for future useful action on such areas as psychology and education research. By linking methodological oversights to estimation results calculated from models (trouble ending, ability to form a conclusion, measure directional impact), this review has practical utility for authors, lecturers, and referees who are in a position to evaluate how seriously applied research should be taken.

6 Conclusion

This systematic literature review reveals that Structural Equation Modeling (SEM), while a powerful statistical tool, presents significant methodological and practical challenges that demand critical attention from researchers. The analysis highlights that errors in model specification remain the most pervasive issue, often resulting from unclear theoretical grounding or incorrect reflective-formative construct assignments. Across the reviewed studies, such specification errors were consistently linked to observable numerical consequences, including convergence failure, inflated standard errors, inadmissible solutions, and instability of path coefficient estimates. These foundational missteps critically undermine the validity of SEM results.

The review further identifies persistent difficulties in model identification and sample size adequacy. Under-identified models and insufficient sample power compromise the stability and interpretability of parameter estimates, especially in highly complex models or those involving second-order constructs. Empirical evidence from the reviewed articles indicates that these conditions frequently manifest as excessive iteration counts, non-convergence, and sensitivity of estimates to minor model respecifications, reflecting fundamental limitations in information sufficiency rather than software malfunction. The dichotomy between Covariance-Based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM) exacerbates these issues, as many studies fail to justify their methodological choices based on research goals, model complexity, or data properties.

Practical concerns, including inadequate reporting standards, limited validation of multivariate assumptions, and inconsistent use of robust reliability and validity metrics, further diminish the reliability of SEM-based research. From a numerical and algorithmic perspective, omissions related to convergence criteria, iteration limits, estimator settings, bootstrapping procedures, and software/version disclosure prevent independent assessment of estimator stability and bias–variance behavior. The frequent omission of essential details, such as the handling of missing data, the independence of observations, and the rationale for fit indices, impedes the transparency and reproducibility of findings across disciplines.

To enhance methodological rigor, this review recommends implementing structured guidelines for SEM application, with an emphasis on model fit evaluation, validity testing, and justification of estimators. Such guidelines should explicitly require

reporting of numerical-stability diagnostics, including convergence behavior, iteration counts, admissibility checks, and resampling settings, enabling reviewers to evaluate whether reported results reflect stable solutions or estimation artifacts. A decision framework to guide SEM type selection based on research intent, data distribution, and sample considerations would significantly reduce methodological misalignment. Moreover, integrating advanced approaches, such as Bayesian SEM, two-step modeling, and cross-validation, provides robust alternatives for handling complex or non-normal data.

Overall, the findings underscore the need for heightened methodological awareness, rigorous model design, and transparent reporting practices among SEM users. By explicitly recognizing the link between methodological decisions and their numerical consequences—such as bias–variance tradeoffs, convergence behavior, and estimator sensitivity—researchers and reviewers can move beyond surface-level fit assessment toward more robust evaluation of SEM validity. Continuous capacity building, adherence to evolving standards, and cross-disciplinary methodological integration will be key in ensuring that SEM continues to serve as a reliable and insightful tool in modern empirical research.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

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