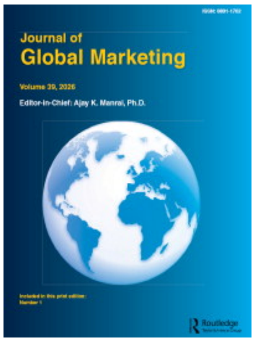

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RESEARCH ARTICLE

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A Multimethod SEM Framework for Analyzing Models with Latent Variables

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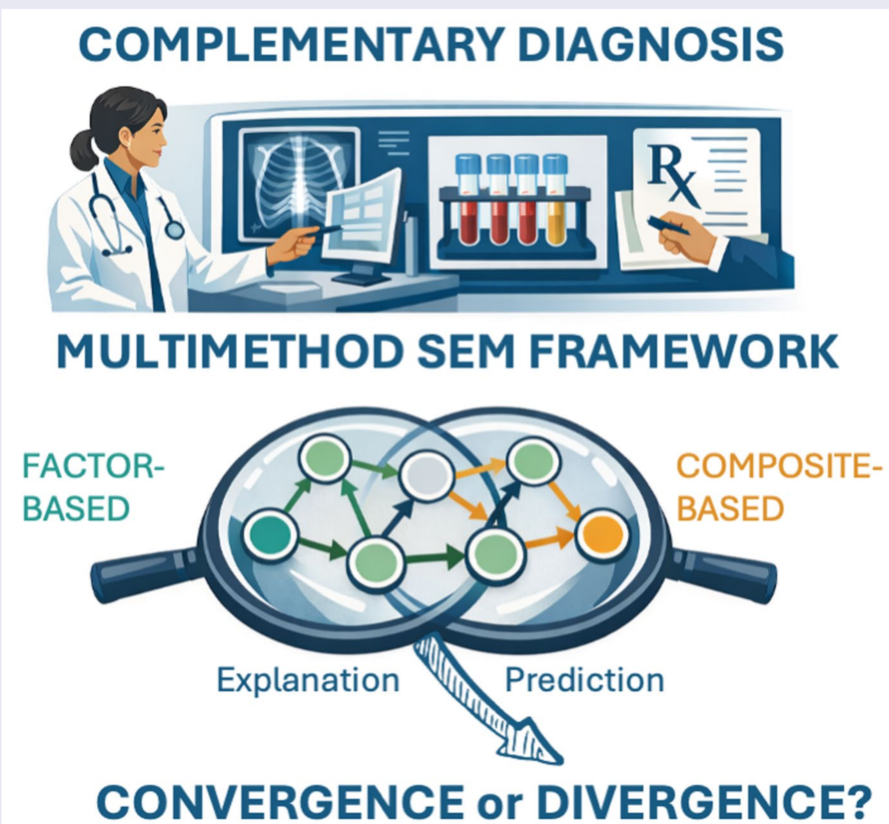
ABSTRACT

Structural equation modeling (SEM) is widely used to estimate relationships among latent variables and their indicator variables. While different approaches exist, researchers often rely on a single estimation tradition – factor-based or composite-based – despite their distinct assumptions, strengths, and limitations. This practice restricts the rigorous evaluation of structural models, particularly for theories that require both explanatory and predictive assessment. This article introduces a multimethod SEM framework that applies factor-based and composite-based estimators to the same model to assess the robustness of structural paths under alternative conceptual and statistical assumptions. We outline a workflow for implementing multimethod estimation and evaluating convergence and divergence in results. This multimethod SEM framework shifts attention from method allegiance to the empirical performance of the model, thereby improving theoretical inference, predictive assessment, and the overall credibility of SEM-based conclusions.

KEYWORDS

Composite-based SEM; explanatory power; factor-based SEM; multimethod SEM; predictive power; structural equation modeling (SEM)

GRAPHICAL ABSTRACT



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Introduction

> *"Each in his own opinion*
>
> *Exceeding stiff and strong,*
>
> *Though each was partly in the right,*
>
> *And all were in the wrong!"*
>
> –John Godfrey Saxe, *The Blind Men and the Elephant* (1873)

Physicians rarely rely on a single tool when diagnosing complex diseases. They recognize that complex diseases have varied symptoms and causes, and that they need to combine methods such as imaging, lab work, and genetic screening to avoid misdiagnosis and capture patterns a single method might miss. Each method has strengths and weaknesses, but their complementarity produces confidence in the diagnosis and guides effective treatment. By contrast, management researchers analyzing complex multivariate data often commit to one statistical method, defending it as sufficient despite its inherent weaknesses. This tendency is most visible in structural equation modeling (SEM), where researchers have shown dogmatic adherence to their preferred methods that has resulted in persistent debates (e.g., Hair et al., 2024b, 2024c; Rönkkö et al., 2023). Like the blind men in Saxe's parable, management researchers relying on a single methodological perspective risk capturing only part of the truth. Only by integrating multiple perspectives can a fuller, more reliable understanding emerge.

SEM methods play a pivotal role in social sciences and marketing by enabling estimation of complex interrelationships between constructs and their indicators (Baumgartner & Weijters, 2020; Sarstedt et al. 2025). By utilizing SEM methods, scholars can empirically test complex structural models in which directional paths represent hypothesized relationships among constructs, thereby linking theoretical logic to empirical evidence in a systematic and rigorous way. Yet when testing these structural relationships, researchers frequently align themselves with one tradition, either factor-based or composite-based SEM,[1] despite the fact that both approaches have well-documented strengths and limitations (Cho et al., 2025; Sarstedt et al., 2016). The choice among factor-based and composite-based approaches, and among their many estimators, introduces variability and subjectivity that can affect structural path estimates, overall inference, and the generalizability of empirical findings across contexts and samples (Buchanan et al., 1998; Sarstedt et al., 2024a; Silberzahn et al., 2018). Prior research has compared SEM traditions on conceptual and empirical grounds (e.g., Cook & Forzani, 2023; Fornell & Bookstein, 1982; Rigdon et al., 2017; Sarstedt et al., 2016), examined alternative estimators (e.g., Boomsma & Hoogland, 2001; Cho et al., 2023; Hair et al., 2017), and surveyed their use in practice (e.g., Baumgartner & Homburg, 1996; e.g., Sarstedt et al., 2022a). This body of work has clarified theoretical underpinnings and tradeoffs; yet, it has also revealed heterogeneous applications and missed opportunities in the application of SEM methods, which differ in various ways.

The first major difference is whether the SEM methods prioritize explanation (theoretical relevance) or prediction (practical relevance) (Sharma et al., 2024). Although these aims are philosophically complementary, they place different empirical demands on SEM methods. Factor-based estimators emphasize explanatory rigor by providing strong in-sample assessments of how well a model structure aligns with data (Hayduk et al., 2007; Zhang et al., 2021), while composite-based estimators are particularly well suited for assessing out-of-sample predictive power (Chin et al., 2020; Cho et al., 2019; Sharma et al., 2023; Shmueli et al., 2019). Importantly, most theories in management are not purely explanatory or purely predictive but instead combine both aims (Gregor, 2006; Sharma et al., 2024; Shmueli & Koppius, 2011). These explanatory–predictive theories seek to account for underlying mechanisms while also providing practically relevant predictions (Gregor, 2006). In the same way that a medical diagnosis must not only explain the underlying condition but also guide treatment, the elements of a structural model (paths) must not only explain theoretical relationships but also help predict outcomes in ways that guide managerial action (Sharma et al., 2024; Shmueli & Koppius, 2011).

The second major difference between the SEM methods concerns whether constructs in a model are conceptualized as common factors or as composites or a mixture of both (Cho et al., 2025). Since the true data-generating process is unknown, each perspective brings distinct implications for how structural equation models are specified and interpreted (e.g., Guenther et al., 2023; Rigdon et al., 2017; Sarstedt et al., 2016). This distinction is not merely philosophical. It can shape how researchers create and assess models to draw inferences about theoretical mechanisms. However, SEM applications in management research often mix these techniques. For example, widely used models such as the American customer satisfaction index (ACSI; Fornell et al., 1996; Morgeson et al., 2023) are routinely estimated in the literature under both factor-based (e.g., Varki & Colgate, 2001) and composite-based paradigms (e.g., Hult et al., 2017), even though each approach implicitly assumes a different data generation model. In practice, researchers sometimes treat the same construct as a common factor and other times as a composite, which can lead to different path estimates, conclusions, and managerial implications.

These major differences highlight a fundamental problem. SEM traditions are often defended as alternatives when in reality they can be complementary. Just as physicians integrate multiple methods to reach a reliable diagnosis, researchers can integrate factor-based and composite-based approaches to build models that are more credible and relevant. Doing so shifts the focus away from method allegiance and toward what truly matters—the model itself.

Motivated by Saxe's parable of the blind men and the elephant, as well as the recent calls in research (Sarker et al., 2025; Sharma et al., 2024; Wellman et al., 2023), the purpose of this article is to advance a multimethod SEM approach that integrates factor-based and composite-based estimators in a single modeling endeavor, describing how their combined use can help produce more theoretically and practically relevant structural models (see also Guenther et al., 2025; Sarstedt et al., 2024a). Specifically, we advocate a "model as the product" perspective, where the proposed structural paths, and their theoretical and practical relevance take precedence over preference to any single methodological tradition. Within this view, factor-based and composite-based estimators are treated as complementary tools that enable scholars to build and evaluate models whose structural paths are both theoretically grounded and practically meaningful.

A multimethod perspective links explanation with prediction, supporting internal validity and theoretical insight while also providing external validity and practical utility. It also serves as a sharper investigative instrument and an important safeguard by allowing researchers to assess the robustness of empirical findings across competing ontological and epistemological assumptions (Wellman et al., 2023). By estimating a model under both paradigms, scholars can identify results that hinge on the factor versus composite conceptualization and flag theoretical claims that may be overly sensitive to modeling assumptions. Conversely, paths that remain stable across frameworks offer stronger evidence for the underlying theoretical relationships. We formalize this perspective by proposing the multimethod SEM framework, where both types of estimators are applied to the same structural model and their results compared, with special attention to convergence (reinforcing confidence) and divergence (requiring resolution) of results at the structural path-level. By explicitly combining methods, clarifying integration decisions, and aligning choices with research objectives, this article provides a roadmap for systematically conducting multimethod SEM. In doing so, we directly answer recent calls to advance multimethod research through systematic, integration-oriented designs (Sarker et al., 2025; Wellman et al., 2023).

Background

Factor-based and composite-based SEM

SEM consists of two broad types of estimators—factor-based and composite-based. The two estimator types differ in how they represent constructs, estimate relationships, and evaluate theoretical versus practical relevance (e.g., Hair et al., 2017; Sarstedt et al., 2024a). Factor-based SEM assumes that the data stem from a common factor model population where the indicator covariances define the nature of the data (e.g., Jöreskog, 1978). To estimate the model parameters, only the common variance—that is, the variance that the indicators of a constructs share—is used (Anderson & Gerbing, 1988; Bollen, 1989; Rigdon, 1998). Maximum likelihood (ML), commonly referred to as covariance-based SEM (CB-SEM), is the main workhorse of this family, but many more variants exist (e.g., Boomsma & Hoogland, 2001). Model assessment in this paradigm focuses on in-sample global fit indices, such as χ^2, CFI, TLI, RMSEA, and SRMR, that capture how well the theoretical structure explains variance and covariance patterns within the sample (e.g., Byrne, 2016; Diamantopoulos & Siguaw, 2000; Hair et al., 2025). Factor-based methods therefore serve as powerful tools for theory confirmation by means of in-sample tests of model congruence (Sharma et al., 2024). However, the inherent indeterminacy of factor-score estimation makes these methods less suitable for predictive assessments (Anderson & Gerbing, 1988), although recent work has sought to overcome this issue (de Rooij et al., 2023).

Composite-based SEM by contrast linearly combines the indicators of each construct's measurement model to compute composite scores (Jöreskog & Wold, 1982; Sarstedt et al., 2016). These composites represent the constructs in the statistical model and serve as proxies for the conceptual variables being examined (Rigdon, 2012, 2023). The methods then use these scores as input to compute the model parameters through a series of regression analyses, with the aim of maximizing the explained variance of the endogenous constructs and their indicators. Correspondingly, model evaluation emphasizes in-sample measures such as the R^2 and f^2, but particular emphasis is placed on establishing the model's out-of-sample predictive power using *k*-fold cross-validation routines such as $\text{PLS}_{\text{predict}}$ (Shmueli et al., 2016), the cross-validated predictive ability test (CVPAT; Liengaard et al., 2021), and out-of-bag-prediction (Cho et al., 2019). The focus here is on "causal prediction," that is, uncovering theoretical mechanisms that aid in predictive or practical relevance. Composite-based methods also provide measures for overall model fit (Hwang & Takane, 2004, 2014), but their efficacy has yet to be broadly analyzed in the literature (Dash & Paul, 2021; Hair et al., 2019; Henseler & Sarstedt, 2013; Schuberth et al., 2023). Various composite-based SEM estimators exist, which differ in the way they determine the indicator weights. Within this paradigm, partial least squares structural equation modeling (PLS-SEM; Lohmöller, 1989; Wold, 1982)[2] and generalized structure component analysis (GSCA; Hwang & Takane, 2004, 2014) represent the most prominent methods.

Researchers have also proposed methods that seek to bridge these two SEM domains. For example, building on Dijkstra's (2010) work, consistent PLS (PLSc) uses the reliability coefficient ρ_A to correct construct correlations for measurement error, under the assumption that the data originate from a common factor model population (Dijkstra & Henseler, 2015). Hwang et al. (2021) developed a corresponding approach within the GSCA framework. Their integrated GSCA (IGSCA) also estimates weighted composites but removes the indicators' unique variance for constructs specified as factors. Research has explored properties and extension of these methods in various ways, for example, by assessing the efficacy of confidence intervals for significance testing (Aguirre-Urreta & Rönkkö, 2018), the performance of model fit metrics (Cho et al., 2022), and introducing regularization to handle collinearity (Cho et al., 2025). Parallel developments have emerged in the factor-based SEM literature, including efforts to specify and estimate hybrid factor–composite structures (Yu et al., 2023).

Although these valuable developments offer researchers additional ways to integrate ideas across SEM traditions, they also highlight the increasing variety of approaches now available, each with its own assumptions and area of appropriate application. To maintain conceptual clarity and provide a shared foundation for our multimethod SEM perspective, we therefore focus on CB-SEM and PLS-SEM as exemplars of the two core approaches most widely used in applied research—see Figure 1 in Hair et al. (2017). Accordingly, while we view the recent methodological advances as valuable additions to the broader SEM toolkit, our aim in this article is to concentrate on CB-SEM and PLS-SEM as the two approaches that remain the most conceptually distinct and most consequential for researchers' theoretical and empirical decisions.

Although CB-SEM and PLS-SEM differ in their assumptions and objectives, they are best viewed as complementary rather than competing approaches (e.g., Jöreskog & Wold, 1982; Rigdon et al., 2017). Importantly, the structural model provides a common space where these paradigms conceptually intersect, since its hypothesized paths can be evaluated through both lenses. When used together, the convergence of evidence across the two approaches offers a more complete assessment of a model's theoretical plausibility and practical relevance. At the same time, instances of divergence between the two can be equally informative by signaling where the underlying modeling assumptions may require closer scrutiny. Next, we discuss how researchers can integrate the strengths of both traditions within a structured workflow tailored to the confirmatory explanatory-predictive mode as depicted by Sharma et al. (2024).

Multimethod SEM workflow in the confirmatory explanatory–predictive mode

Researchers using SEM often face a central methodological challenge. While their theoretical models are designed to explain why relationships occur, the same models are also expected to predict outcomes that are meaningful in practice. Yet, social science researchers regularly overlook predictive aspects of their models (Hofman et al., 2017, 2021). One potential reason is that the dual objectives of explanation and prediction are philosophically complementary but empirically distinct (Gregor, 2006; Sharma et al., 2024; Shmueli & Koppius, 2011). Explanation provides internal validity by using in-sample tests to confirm whether a model aligns with established theory, while prediction provides external validity by testing whether the model can accurately generalize to unseen or out-of-sample data (Shmueli & Koppius, 2011). Sharma et al. (2024) formalized this dual purpose in the explanatory–predictive conceptualization, which helps researchers confirm both theoretical and practical relevance within the same study.

In the confirmatory explanatory–predictive mode, models are developed deductively from existing theory and are then subjected to rigorous empirical testing for confirming both explanatory and predictive adequacy. This mode aligns with the dominant logic of management and marketing research, where models are typically grounded in established constructs and hypotheses, yet are expected to produce results that also inform managerial decision making (Sharma et al., 2024). A purely explanatory perspective may provide deep theoretical insight but limited practical guidance, while a purely predictive perspective may perform well in practical situations but fail to inform theory. Further, statistical significance of a construct, which is a sign of its theoretical relevance, does not automatically lead to its predictive relevance (Lo et al., 2015). In contrast, a highly predictive construct may not have statistical significance. Hence, both theoretical and practical relevance are necessary for cumulative and applied progress (Hofman et al., 2017, 2021; Sarstedt & Danks, 2022; Shmueli & Koppius, 2011).

In Table 1, we adapt Sharma et al.'s (2024) two-dimensional conceptualization, which links in-sample and out-of-sample outcomes to show how theoretical and practical relevance of structural model paths can be evaluated jointly within the confirmatory explanatory–predictive mode. This conceptualization examines the explanatory and predictive evidence for each substantive hypothesized structural relationship that is central

Table 1. Theoretical and practical relevance in the confirmatory explanatory–predictive mode (adapted from Sharma et al., 2024).

		In-sample tests (explanation)	
		Not significant	Significant
Out-of-sample tests (prediction)	Not significant	*Case 1*: Path is not relevant - Does not confirm explanation - Does not confirm prediction	*Case 2*: Path is theoretically relevant but could be overfitting to noise - Confirms explanation - Does not confirm prediction
	Significant	*Case 3*: Path is practically relevant but suggests hidden explanatory mechanisms - Does not confirm explanation - Confirms prediction	*Case 4*: Path is theoretically and practically relevant - Confirms explanation - Confirms prediction

to the model under study, while acknowledging that relationships already well established in prior literature may not require the same degree of confirmatory scrutiny (Sharma et al., 2024). Importantly, our approach assumes that researchers have checked data distribution assumptions and conducted data-related requisite checks (e.g., missing values, extreme observations, Heywood cases), as relevant to each SEM type, before embarking on the multimethod SEM analysis. We encourage readers to refer to the expansive literature in this area (e.g., Chin, 1998; Diamantopoulos & Siguaw, 2000; Rigdon, 1998; Tenenhaus et al., 2005). It also requires that researchers have already conducted appropriate measurement model assessments (construct validity assessments) and overall model-level diagnostics to ensure a sound structural foundation using established guidelines (e.g., Hair et al., 2026; Kline, 2023; Rigdon, 1998; Sarstedt et al., 2025). At the overall model level, model fit and explained variance assessments are used to evaluate the explanatory adequacy of the proposed model while overall model-level predictive evaluations can be conducted to assess its out-of-sample predictive power (Liengaard et al., 2021). These diagnostics collectively help establish that the model is defensible both explanatorily and predictively.

Once these steps are complete, the researcher can shift attention to the path level and provide stronger confirmatory evidence for theoretical advancement by using our multimethod SEM framework to evaluate paths through explanatory and predictive lenses.

A path-level focus is warranted because the structural paths in a model are the primary carriers of theoretical meaning and predictive value. Model-level metrics such as global fit or overall explained variance serve primarily as diagnostic gatekeepers that answer a basic question: Is the overall model a good representation of the underlying data? Yet these global indices provide limited insight into which individual structural relationships meaningfully advance theory or prediction. More specifically, research has noted that global fit measures can conceal weak or incorrect causal relationships and emphasized that accurate inference depends on evaluating the strength and plausibility of specific structural links (e.g., Stone, 2021; Tomarken & Waller, 2003). Research in the prediction literature further strengthens the focus on paths. Yarkoni and Westfall (2017) demonstrate that prediction can reveal weaknesses in individual relationships that are not apparent from overall model performance and that variable-level predictive evaluation is essential for identifying relationships that generalize beyond the sample. Similarly, Ward et al. (2010) show that models, which perform well from an inference perspective, may contain individual variables that add no predictive value. Conversely, variables with modest significance may carry the bulk of a model's predictive capacity (Shmueli & Koppius, 2011). This literature recommends focusing on the predictive contribution of each variable asking not whether the model performs well, but whether each variable contributes meaningfully.

Such an assessment can be realized by comparing the hypothesized model with a nested model that omits a specific path, thereby isolating the incremental predictive contribution of that relationship. Importantly, weak overall model-level predictive performance does not imply that all of the model's constituent paths are predictively useless (Ward et al., 2010). Because overall tests aggregate all relationships, predictive signals at the model-level can be affected by weak paths that add more noise than signal (Yarkoni & Westfall, 2017). Path-level assessments can help diagnose such situations by identifying relationships that enhance or dilute performance. Path-level tests thereby act as a triangulation device. Overall model level predictive assessment establishes whether the theory has practical relevance as a whole, while path level assessment provides the resolution needed to understand how predictive relevance is gained or lost within that system. Within the multimethod SEM workflow, therefore, the global model-level tests help establish the overall structural foundation. Once these prerequisites are met, the framework shifts attention to the path level because theoretical advancement depends on identifying which structural relationships matter theoretically and predictively.

Applying this logic to the multimethod SEM framework, the central question then becomes "Which paths truly matter, theoretically and predictively?" The four cases in Table 1 help to answer this question by illustrating how explanation and prediction can be confirmed together within the confirmatory explanatory–predictive mode.

Case 1 indicates that a path has no theoretical or practical value. This means the hypothesized relationship likely lacks conceptual support, and the researcher should consider either its removal or an adjustment of the underlying theory.

Case 2 represents theoretical relevance without predictive support which could potentially be a signal of overfitting. In this situation, the researcher should examine whether the model is too tightly fitted to the specific sample or whether omitted variables or measurement issues are limiting predictive accuracy.

Case 3 captures practical relevance without explanatory support, suggesting that an unexplained mechanism may be at work. The researcher encountering this case should treat it as an opportunity for theory development by exploring boundary conditions or hidden mediators that can explain the observed practical effect.

Case 4 is the ideal outcome in which the path enhances both explanation and prediction, thereby confirming its importance for both theory and practice.

Building on these considerations, we next discuss how CB-SEM and PLS-SEM can be combined within a multimethod SEM framework to operationalize these ideas in empirical SEM applications. We outline how it applies both estimator types to assess path coefficient stability under different data-generating assumptions (i.e., factor-based and composite-based) before proceeding to out-of-sample prediction using composite-based SEM. Table 2 summarizes the workflow step by step.

The multimethod SEM framework proceeds through a series of coordinated steps. Researchers begin by specifying the model and estimating it using CB-SEM to evaluate model fit and the significance of structural paths. The structural model is then estimated using PLS-SEM to evaluate the same paths from a different epistemic and computational logic. This dual estimation makes it possible to compare the outcomes of both estimators for each relationship in the model and to determine whether the results converge. After the in-sample comparison, PLS-SEM is used for out-of-sample prediction to test whether the model maintains predictive performance beyond the sample data. The results are then integrated within the explanatory–predictive perspective to interpret both convergence and divergence across estimators.

This workflow explicitly reveals estimator dependence of in-sample results. Agreement between CB-SEM and PLS-SEM suggests that results are not driven by methodological artifacts, while disagreement signals potential issues in model specification. Table 3 summarizes the

Table 2. Step-by-step guideline for multimethod SEM framework for confirmatory explanatory–predictive mode.

Step	Description
Initial preparatory steps	
1. Specify the model based on theory-based deduction.	Define constructs and hypothesize paths in the model based on theory and logic.
2. Conduct requisite data distribution checks.	Check data distribution assumptions and conduct data-related requisite checks (e.g., missing values, extreme observations, Heywood cases), as relevant to each SEM type.
3. Establish measurement model quality.	Apply measurement model quality criteria to assure the reliability and validity of constructs using the established guidelines.
4. Empirically validate the overall model structure for explanatory and predictive validity.	Assess model fit using CB-SEM and explained variance (R^2) using PLS-SEM based on the established guidelines to establish overall model-level explanatory adequacy. Assess overall model-level predictive validity using out-of-sample tests such as CVPAT.
Multimethod workflow steps for assessing individual structural paths	
5. Assess the structural model for in-sample explanation using factor-based estimator.	Assess the structural path significance and size using CB-SEM based on the established guidelines.
6. Assess the structural model for in-sample explanation using composite-based estimator.	Assess the structural path significance and size using PLS-SEM based on the established guidelines.
7. Compare in-sample results.	Compare the path-level CB-SEM and PLS-SEM in-sample results. Interpret convergence and divergence of in-sample results using Table 3.
8. Conduct out-of-sample prediction test using composite-based estimators.	Utilize CVPAT or related out of sample tests to assess predictive validity by comparing the hypothesized model with an otherwise identical nested model that excludes the focal path under consideration, thereby isolating the predictive contribution of that path.
9. Integrate explanation with prediction.	Interpret results across CB-SEM and PLS-SEM. Map findings to the cases 1–4 in Table 1. Report estimator convergence/divergence transparently.

Table 3. Interpreting convergence and non-convergence across estimators.

Explanatory testing (in-sample)				Predictive testing (out-of-sample)		Implications	
In-sample pattern	In-sample result for a path in the model (hypothesis)	Explanatory implication	Theoretical relevance	CVPAT results for a path in the model (hypothesis)	Predictive relevance	EP-mixed quadrant (Table 1)	Researcher guidance
Convergent	Both CB-SEM and PLS-SEM are significant	Consistent in-sample evidence across estimators indicates robust empirical support for the hypothesized relationship under both factor-based and composite-based assumptions.	Strong support	Significant	Predictive relevance validated	**Case 4:** Strong theoretical and practical relevance established. Robust effect, supported by theory and validated in prediction.	Robust effect across explanation and prediction. Highlight as central to both theory and practice.
				Not Significant	Predictive relevance not validated	**Case 2:** Theoretical relevance only. Effect is theory-consistent but lacks predictive utility.	Effect is strong in theory but not practically useful. Report as theory-driven explanation. Avoid predictive claims.
	Both CB-SEM and PLS-SEM are **not** significant	No in-sample support from either estimator. Effect likely absent or trivial.	No support	Significant	Predictive relevance validated	**Case 3:** Practical relevance only. Effect adds predictive utility without theoretical support. May indicate hidden mechanisms or misspecification.	Unexplained predictive-only effect. Treat as hypothesis generating. Reexamine theory, construct conceptualization, or measurement to identify potential hidden mechanisms.
				Not Significant	Predictive relevance not validated	**Case 1:** Neither theoretical nor practical relevance. No evidence for the effect.	Absence of any effect in the current sample. Deprioritize or remove path unless strong justification to retain exists.
Divergent	CB-SEM is significant, PLS-SEM is **not** significant	In-sample evidence exists but is contingent on estimator assumptions, indicating sensitivity to construct conceptualization or population model.	Estimator-contingent in-sample support	Significant	Predictive relevance validated	**Case 4:** Theoretical relevance with estimator sensitivity flagged. Predictive relevance is established, but in-sample support is not robust across estimators.	Report as explanatorily supported under factor-based assumptions only and predictively useful. Emphasize that in-sample confirmatory support is provisional. Explicitly flag estimator sensitivity and recommend replication, respecification, or triangulation. Optionally utilize a triangulation method to adjudicate.
				Not Significant	Predictive relevance not validated	**Case 2:** Theoretical relevance with estimator sensitivity flagged. In-sample evidence exists under one estimator but lacks out-of-sample predictive relevance.	Report as explanatorily supported under factor-based assumptions only. Emphasize that in-sample confirmatory support is provisional. Explicitly flag estimator sensitivity and recommend replication, respecification, or triangulation. Optionally utilize a triangulation method to adjudicate. Avoid any predictive claims.
	CB-SEM is **not** significant, PLS-SEM is significant	In-sample evidence exists but is contingent on estimator assumptions, indicating sensitivity to construct conceptualization or population model.	Estimator-contingent in-sample support	Significant	Predictive relevance validated	**Case 4:** Theoretical relevance with estimator sensitivity flagged. Predictive relevance is established, but in-sample support is not robust across estimators.	Report as explanatorily supported under composite-based assumptions only and predictively useful. Emphasize that in-sample confirmatory support is provisional. Explicitly flag estimator sensitivity and recommend replication, respecification, or triangulation. Optionally utilize a triangulation method to adjudicate.
				Not Significant	Predictive relevance not validated	**Case 2:** Theoretical relevance with estimator sensitivity flagged. In-sample evidence exists under one estimator but lacks out-of-sample predictive relevance.	Report as explanatorily supported under composite-based assumptions only. Emphasize that in-sample confirmatory support is provisional. Explicitly flag estimator sensitivity and recommend replication, respecification, or triangulation. Optionally utilize a triangulation method to adjudicate. Avoid any predictive claims.

interpretation of convergence and divergence across the two estimation paradigms.

The interpretation of convergence and non-convergence helps researchers distinguish between robust and unstable findings. When both estimators identify a path as significant and prediction confirms its relevance, the result represents the strongest form of evidence in the confirmatory explanatory–predictive mode (see also Sharma et al., 2024). Conversely, when estimators disagree, the researcher must interpret the result carefully. These outcomes should be reported transparently as they offer insight into where theoretical refinement or model re-specification may be necessary.

When results diverge substantially, researchers may consider utilizing another triangulation method to gain further insight. For example, IGSCA combines factor and composite logic within a single method (Cho et al., 2022; Hwang et al., 2021), making it well suited for evaluating discrepancies between estimation traditions. Alternatively, building on prior work by Ogasawara (2007), the Henseler-Ogasawara approach (Henseler, 2021) offers a specification for incorporating composites within a factor based approach (Yu et al., 2023), providing another viable perspective when triangulation is needed. Together, these methods offer a third viewpoint for assessing whether discrepancies stem from estimator assumptions or reflect genuine model differences. Although not definitive arbiters, they provide practical means for probing and potentially resolving disagreements between factor-based and composite-based estimators.

Discussion and conclusion

A model that explains without predicting is incomplete for practice, just as a diagnosis that explains symptoms without guiding treatment is incomplete for medicine. Yet management research has overwhelmingly relied on in-sample explanatory assessments while making out-of-sample predictive claims (Sharma et al., 2024; Shmueli, 2010; Shmueli & Koppius, 2011). As Hofman et al. (2017) and Hofman et al. (2021) argue, models that explain without demonstrating predictive utility risk limited generalizability and contribute little to managerial decision making. Within marketing, this concern has long been recognized. Steenkamp and Baumgartner (2000) emphasized that the relevance of theoretical explanations is ultimately tested by their ability to predict the consequences of marketing actions.

In contrast, a sole focus on prediction without theoretical grounding, an approach frequently observed in machine learning applications in the context of big data, also risks leading researchers to superficial or misleading conclusions, for example when inferences are drawn from spurious or unexplainable correlations (Kübler et al., 2025). Thus, it is the integration of explanation and prediction that constitutes a central pillar of future quantitative research in the social sciences. The explanation perspective provides the theoretically and logically grounded justification for the relationships under investigation, while the prediction perspective enhances the practical usefulness of theoretical models by demonstrating their out-of-sample relevance.

The multimethod SEM approach advanced in this paper addresses this limitation by combining explanatory and predictive evaluation with the assumptions of population model for the constructs. CB-SEM assumes a common factor model in which shared covariation among indicators reflects an underlying latent trait. PLS-SEM assumes a composite population in which indicators are linearly combined to form construct scores that serve as proxies for conceptual variables. Treating these approaches as interchangeable is not recommended because each embeds distinct assumptions about how constructs exist, how they should be measured, and how structural relationships should be interpreted (Hwang et al., 2023).

Our multimethod SEM framework therefore does more than cross check two estimation procedures. It asks whether a structural path is robust to both (1) differences in explanatory and predictive objectives and (2) differences in construct conceptualization grounded in factor and composite logic. It empowers researchers to pursue different modeling objectives using estimators suited to those objectives. While CB-SEM excels at internal validity and at capturing the theoretical structure of the population, PLS-SEM stands out in terms of assessing predictive accuracy and practical relevance. When applied together to conduct path-level analysis, they yield structural models with both theoretical meaning and practical usefulness. Furthermore, when a path is stable across CB-SEM and PLS-SEM, this suggests that the underlying theoretical linkage is not an artifact of a population model assumption. When the pattern of path level results diverges across estimators, it offers insight into how theoretical assumptions interact with modeling choices. It may indicate that a construct implicitly treated as a common factor behaves in practice like a composite (or vice-versa), that the measurement model is misaligned with the construct's conceptual definition, or that the structural relationship depends on a specific operationalization that does not generalize.

This dual focus reframes the interpretation of convergence and divergence. Convergence across CB-SEM and PLS-SEM, combined with strong explanatory and predictive performance, strengthens confidence that the theorized mechanism is both conceptually sound and practically useful. Divergence, by contrast, becomes theoretically informative rather than merely inconvenient. It invites researchers to ask whether the construct has been misspecified (factor vs composite), the measurement model is misaligned with the conceptual definition, or the structural path is being affected by a particular method adversely. When substantial discrepancies arise, additional triangulation tools such as IGSCA (Cho et al., 2022; Hwang et al., 2021) or Henseler-Ogasawara specification (Yu et al., 2023) can help determine whether the disagreement originates in estimator assumptions or reflects genuine differences in how the constructs are generated in the population.

The multimethod SEM perspective is aligned with broader methodological calls for multimethod research in the social sciences (Sarker et al., 2025; Wellman et al., 2023). These scholars emphasize that triangulation enriches meta inferences, enhances credibility, and supports a balance between internal and external validity. Our framework brings this vision to SEM by positioning analytical methods as diagnostic tools for refining the model as the primary scholarly product. The goal is to encourage researchers and reviewers to look beyond the defense of a particular analytical method and to develop models whose structural paths retain their meaning and relevance under plausible assumptions about the data generating process and the intended use of the model. This method-agnostic view echoes the complementary vision articulated by Jöreskog and Wold (1982) who viewed factor and composite-based approaches as offering distinct but synergistic insights.

Readers may well ask whether we are strongly against relying on a single estimator in empirical studies in all cases. We are not. However, we argue that exclusive reliance on a single estimator can be limiting and may obscure important aspects of empirical inference, particularly when researchers face uncertainty about the underlying data-generating process and pursue multiple inferential objectives. It may also create a misguided sense of confidence in the implications of a study or result in fragmented implications driven by estimator-specific variation across studies in a field. Importantly, this source of variation reflects differences in modeling assumptions and estimation principles rather than deficiencies of a particular method. Thus, such variation is not inherently attributable to any one estimation tradition but can arise under both factor-based and composite-based approaches (Sarstedt et al., 2024a). The resulting fragmentation in the field can be difficult to reconcile because estimator-specific variation can be conflated with substantive theoretical differences or sample-specific characteristics. The multimethod SEM approach can help guard against such misattribution by making this variability more transparent and by encouraging triangulation across complementary estimation paradigms.

At the same time, we acknowledge that different methodological approaches may encounter technical or practical limits under certain conditions, including data characteristics, model complexity, and estimation constraints (e.g., Hair et al., 2026; Sarstedt et al., 2016, 2024a). When this occurs, researchers should treat such limitations as diagnostically informative rather than as reasons to default uncritically to a single estimator. For example, when a given estimator fails to converge or proves unsuitable under specific data or model conditions, researchers can still triangulate their findings by applying alternative estimators that rely on different modeling assumptions and estimation principles. In particular, the benefits of triangulation are maximized when estimators are drawn from both factor-based and composite-based paradigms.

From this perspective, the multimethod SEM approach spanning factor-based and composite-based estimators provides a more transparent mechanism for triangulating, reporting, and interpreting empirical findings. Thus, we suggest that researchers should generally not rely on a single method or paradigm but instead leverage the complementary strengths of a multimethod approach when they can. Moreover, adopting the multimethod SEM approach is increasingly feasible in practice. Recent advances in SEM software and open-source packages have substantially lowered the technical and computational barriers to implementing multiple SEM estimators within the same study.

Beyond its immediate implications for empirical inference, embracing the multimethod SEM approach opens up new avenues for methodological development. As researchers apply multimethod SEM in diverse empirical settings, important questions will inevitably arise regarding its scope, implementation, and interpretation. For example, while the proposed framework is applicable to different types of relationships, including moderation and other higher-order effects, individual SEM methods may reach technical or practical limits under certain conditions (e.g., model complexity or estimation constraints). Accordingly, a key boundary condition of the framework arises when the assumptions or requirements of a method cannot be adequately met. We do not claim to anticipate or resolve all such issues at this stage. Rather, we view the multimethod SEM framework as an evolving research program that invites further refinement, critical evaluation, and extension as scholars gain experience with its application across different research contexts.

In future research, we anticipate that the multimethod SEM framework will be broadly applied across the social sciences, including marketing contexts such as the widely used ACSI model (Fornell et al., 1996; Morgeson et al., 2023). In addition to its application in studies, the multimethod SEM framework invites future research to extend triangulation to additional complementary methods (for an overview, for example, see Gudergan et al., 2025). Techniques such as necessary conditions analysis (NCA; Becker et al., 2026; Dul, 2016; Richter et al., 2020), importance–performance map analysis (IPMA; Hair et al., 2024a; Ringle & Sarstedt, 2016), combined approaches such as cIPMA (Hauff et al., 2024; Sarstedt et al., 2024b), tools for detecting observed and unobserved heterogeneity (e.g., FIMIX-PLS and PLS-POS; Becker et al., 2013; Sarstedt et al., 2011; Sarstedt et al., 2022b; Sarstedt et al., 2017), and identifying and treating endogeneity issues (e.g., Becker et al., 2022; Liengaard et al., 2025) can further enrich explanatory–predictive evaluation and support more nuanced theoretical claims.

Future research should also seek to develop criteria that consider the tradeoffs between prediction and explanation when modifying models (e.g., increasing model complexity may increase a model's explanatory power while decreasing its predictive power). Such a development could also inform model search algorithms that systematically explore theoretically admissible model specifications and enable benchmarking a given model against the best-performing alternative within the explanation-prediction space.

Finally, the proposed multimethod SEM framework is consistent with recent calls (e.g., Guenther et al., 2025; Sarstedt et al., 2024a; Sharma et al., 2024) to revitalize the original complementary perspective underpinning CB-SEM and PLS-SEM. Rather than viewing these methods as competitors, the multimethod SEM framework positions them as partners in ensuring that conclusions rest on both theoretical coherence and predictive relevance as two sides of the same coin. We hope this work contributes to a future in which SEM research prioritizes robustness, transparency, and practical usefulness through systematic multimethod inquiry.

Notes

1. In prior research, the terms composites and components have been used interchangeably when referring to methods such as PLS-SEM and GSCA (e.g., Guenther et al., 2023; Hair et al., 2024b; Hwang et al., 2020; Sarstedt et al., 2024a). To maintain consistency for our readers, we use the term composite throughout in this manuscript.
2. PLS-SEM is also referred to as path models with latent variables (Wold, 1975), partial least squares (PLS; Wold, 1985), latent variable path modeling with partial least squares (Lohmöller, 1989), PLS path modeling (Tenenhaus et al., 2005), and the PLS approach to structural equation modeling (Chin, 1998) in the literature – see Gudergan et al. (2025).

Authors' contributions

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