# TRENDS IN SEM UTILIZATION AND REPORTING PRACTICES IN THAI BUSINESS RESEARCH (2020-2024): A SYSTEMATIC LITERATURE REVIEW

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## ABSTRACT

This research adopted a systematic literature review methodology to analyze trends in SEM utilization and reporting practices within Thai business research from 2020 to 2024. A well-established seven-step process guided the review. First, the research questions were defined: 1) to identify business articles employing SEM analysis and 2) to analyze trends in SEM type application. Second, the TCI Group 1 database and 14 relevant business journals were chosen. Step 3 utilized the keywords "SEM" and "Structural Equation Model" for the search. The initial search yielded 214 articles, which underwent a rigorous screening and assessment process (steps 5-7). This review process revealed key findings: 1) a rising trend in covariance-based SEM (CB-SEM) use and a decline in variance-based SEM (VB-SEM), 2) a prevalence of complex models with constructs for abstract variables and mediating effects, 3) inconsistent reporting of direct and indirect effects in articles using mediating variables, 4) a lack of documented discriminant and construct validity in approximately half the articles, particularly those employing CB-SEM, and 5) concerning deviations from accepted statistical procedures in model modifications (47.73%).

**Keywords:** SEM, Systematic Literature Review, Mediating Variable, Construct Validity, Discriminant Validity

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# INTRODUCTION

Structural Equation Modeling (SEM) is one of the most salient research methods across a variety of disciplines, especially SEM is a powerful tool for business Research. SEM also known as covariance structural analysis, is a popular statistical technique widely used in business research to estimate parameters and analyze theoretical relationships with empirical data. It comprises two essential components: measurement model analysis and structural model analysis (Schumacker & Lomax, 2010; Hair et al., 2010). The unique combination of features in these two research model components makes SEM a statistical analysis method compared to other approaches employed in business model creation. In essence, SEM serves as a powerful research tool for evaluating theories and refining models to enhance their contextual relevance (Dejan & Darja, 2014).

Currently, there are two primary approaches to parameter estimation in SEM statistics: 1) Covariance-Based SEM (CB-SEM): This approach estimates parameters using the maximum likelihood method, examining the congruence between the theoretical covariance structure and the empirical covariance structure of the data. It represents a hypothesis-testing approach, also known as confirmatory SEM techniques (Hair et al., 2018; Kline, 2023). 2) Variance-Based SEM (VB-SEM): This approach estimates parameters using the partial least squares (PLS) method, aiming to minimize error variance and identify statistically significant predictors of the dependent variable. This approach is referred to as exploratory SEM techniques (Asparouhov & Muthén, 2009; Marsh et al., 2014). The choice between CB SEM and VB SEM depends on the research objectives and the nature of the data. CB SEM is suitable for testing well-established theories and refining existing models, while VB SEM is more appropriate for exploring new relationships and identifying key predictors in complex models (Hair et al., 2018). In conclusion, SEM offers a versatile and powerful tool for business researchers to develop, test, and refine their models, enabling them to gain deeper insights into complex business phenomena and make informed decisions that drive business success.

Business research serves as a cornerstone of informed decision-making within the contemporary corporate environment. By systematically gathering, analyzing, and interpreting data, businesses gain a crucial understanding of their target markets, competitive landscape, and internal operations. This understanding empowers them to navigate the complexities of the marketplace and achieve sustainable success. Business research encompasses a broad spectrum of topics and methodologies, encompassing diverse aspects of business operations, market dynamics, and consumer behavior. Key areas of focus within business research include Market Research, Organizational Behavior and Management, Financial and Economic Analysis, Operations Management and Supply Chain, Innovation and Entrepreneurship, etc. These areas represent a part of the diverse topics encompassed within business research. The specific focus of business research projects varies depending on the research questions, objectives, and industry context. Thai researchers often publish their research articles through journals that are recognized as meeting the standards according to the citation criteria of the Thai Journal Citation Index Center (TCI). This research paper aims to conduct a systematic literature review (SLR), which is a type of research methodology commonly used in the social sciences (Sambunjak et al., 2017). The primary objective of an SLR is to systematically gather and analyze existing research studies to identify patterns, trends, or emerging themes. By synthesizing previous research, SLRs provide a comprehensive overview of a particular research topic and can be used to inform future research directions and decisions-making to new research. This research demonstrates the trend of using SEM in different time periods. Additionally, the findings from the content analysis of past research that have applied SEM, including recommendations, will be beneficial to researchers in business branch and related. This research goal is review and analyze the use of SEM in Business research include the period 2020-2024.

## LITERATURE REVIEWS

### Principle and Concept of SEM

SEM techniques to analyze data in business research has become increasingly popular (Krit, 2024). Examples of business research using SEM include Meathawiroon (2023) that study model of logistics service quality, image, trust and loyalty of food delivery service. CB-SEM was being used to test the research hypothesis. Pitjatturat and Runkawee (2023) to study the influence of online relationship marketing on customer engagement, and to study the influence of customer engagement on customer loyalty toward mobile phone network service providers in Thailand by VB-SEM or PLS-SEM.

SEM emerges as a robust multivariate technique that integrates elements of multiple regression and confirmatory factor analysis (Hair et al., 2010; Schumacker & Lomax, 2010). Similar to multiple regression, SEM examines dependence relationships; however, it extends this capability by simultaneously estimating a network of interrelated dependencies. This synergistic approach mirrors confirmatory factor analysis by incorporating latent variables, which represent underlying constructs measured through multiple observed variables (McDonald & Ho, 2002). Consequently, SEM surpasses traditional path analysis by explicitly accounting for measurement error and latent constructs. Within the behavioral and social sciences, SEM has become a prevalent method for depicting theoretical models encompassing both direct and indirect relationships between independent and dependent variables.

In sum, SEM is a statistical technique that integrates two distinct, yet interrelated, components: the measurement model (MM) and the structural model (SM). The MM plays a crucial role in establishing the link between latent variables, which are theoretical constructs, and their observed indicators, which are the measured data points. The primary function of the MM is to assess the reliability and validity of the measures used to represent the latent variables in the research model. The SM represents the core theoretical relationships hypothesized to exist between latent variables. The SM depicts the hypothesized causal or associational linkages between latent variables, which are underlying constructs not directly observable. The SM is the heart of theory testing in SEM. It allows researchers to statistically assess the validity of the hypothesized relationships between the latent variables. It allows for the simultaneous estimation of multiple relationships within a single model, providing a more comprehensive understanding of the complex relationships between latent variables. However, the validity of the SM heavily relies on the quality of the MM, which defines how the latent variables are measured by the observed variables (Hair et al., 2010; Schumacker & Lomax, 2010).

### Types of SEM

There are primarily two main approaches to parameter estimation in SEM commonly employed in business research; firstly, CB-SEM, this approach focuses on testing well-established theories and refining existing models. CB-SEM utilizes the maximum likelihood method. This method estimates parameters by finding the set of values that maximizes the likelihood of observing the actual data, given the hypothesized model structure. CB-SEM emphasizes the congruence between the theoretical covariance structure implied by the hypothesized model and the empirical covariance structure derived from the observed data. CB-SEM provides a rigorous test of theoretical relationships and allows for hypothesis testing (Schumacker & Lomax, 2010).

CB-SEM requires strong theoretical foundation, adherence to assumptions of normality and linearity in data, and may be less suitable for exploratory research. This view of CB-SEM is, however, very limited given that VB-SEM constitutes a second string in SEM, which is growing in popularity among business researchers. This approach is more appropriate for exploring new relationships and identifying key predictors in complex models. VB-SEM employs the partial least squares (PLS) method. This method focuses on minimizing the error variance in the predicted values of the dependent variables. It prioritizes identifying the most relevant predictors of the dependent variables, even if the overall model fit is not perfect. Strengths of VB-SEM is more flexible with data assumptions, particularly useful for exploratory research, and handles complex models with many latent variables well. Limitations, However, of VB-SEM is less emphasis on hypothesis testing and theory confirmation compared to CB SEM (Hair et al., 2021).

**Considerations for Selecting CB-SEM and VB-SEM in Business Research**

Researchers conducting business research using SEM should carefully consider their research objectives and data characteristics when selecting between CB-SEM and VB-SEM (Hair et al., 2017; Hair et al., 2021).

**CB-SEM for Confirmatory Research:**

Strengths of CB-SEM is well-suited for confirmatory research aiming to validate established theoretical frameworks, encompassing both structural and measurement models. It emphasizes the analysis of common variance shared by observed variables and underlying latent constructs. Additionally, CB-SEM aligns with a common factor model where only common variance is considered for estimation. It prioritizes global goodness-of-fit criteria to assess overall model-data congruence. However, CB-SEM may require additional error term specifications to capture nuanced relationships beyond the main model. It is typically applied to statistically tractable models with a moderate level of complexity, involving a maximum of five latent constructs and 50 indicator variables. In sum, CB-SEM excels in confirmatory research with well-developed theoretical foundations, emphasizing common variance, global fit assessment, and potentially requiring additional error term specifications. It is often applied to models with moderate complexity.

**VB-SEM for Exploratory Research and Complex Models**:

Strengths of VB-SEM excels in exploratory research where the primary aim is to identify novel relationships and understand underlying phenomenon structures. While it can be used for confirmation, its focus lies on total variance explained rather than exact model fit. VB-SEM prioritizes prediction by identifying the most relevant predictors of dependent variables. It effectively handles complex models with numerous constructs (6 or more) and a high number of indicators (50 or more) per construct. VB-SEM can accommodate formative constructs where the latent variable is defined by its indicators. Furthermore, VB-SEM places less stringent assumptions on normality and is suitable for smaller sample sizes (less than 100) while remaining valuable for larger samples. Summary, VB-SEM offers a versatile approach for exploring new relationships, prioritizing prediction, handling complex models, small samples, non-normal data, or ordinal/nominal response scales.

**Systematic Literature Review**

SLR offer a rigorous and independent method to comprehensively identify and critically evaluate relevant literature on a specific topic. This approach synthesizes existing knowledge, yielding well-founded conclusions on the research question. By systematically analyzing current research, SLRs illuminate the field's current state of knowledge and expose potential gaps or areas for further exploration (Booth et al., 2012).

SLR minimize bias through a transparent framework. This includes pre-defined inclusion/exclusion criteria and a meticulously designed search strategy aligned with the research question. Electronic databases are the primary source, but manual searches of relevant reference lists supplement this for a holistic understanding (Tranfield et al., 2003).

Characteristics of SLR were independent research method, explicit formulation of the search objectives, identification of all publications on a topic, defined criteria for inclusion and exclusion of publications, description of search procedure, literature selection and information extraction by several persons, and transparent quality evaluation of publications. (Petticrew & Roberts, 2006; Ridley, 2012). The concept of a Systematic Literature Review (SLR) encompasses a variety of process stages, with differences noted in their definitions across the

scholarly literature (Tranfield et al., 2003; Ridley, 2012). However, within the context of business research, this study, so, adopts the seven-following sequenced of steps (Briner & Denyer, 2009; Guba, 2008; Bandara et al., 2015; Fink, 2014).
Step 1: Defining research questions
Step 2: Selecting databases and other research sources
Step 3: Defining search terms
Step 4: Merging hits from different databases
Step 5: Applying inclusion and exclusion criteria
Step 6: Perform the review
Step 7: Synthesizing results

## RESEARCH METHODOLOGY

This research employs a systematic literature review (SLR) methodology, drawing upon existing scholarly literature within the business research domain. The objective is to provide a comprehensive historical overview of how structural equation modeling (SEM) has been utilized as a data analysis tool in Thai business journals. The review process adheres to a seven-step approach established through a prior review of relevant literature.
**The initial step** involved formulating the primary research question: How do business research published in journals in Thailand utilize SEM to analyze data? And, how does the trends in using each type of SEM?
**The second step** was database selection. We reputable academic database recognized by Thai scholars was chosen for the literature search. We mean the Thai Journal Citation Index Center (TCI-Center) database, which special is currently classified in Group 1. And to be more specific, we selected journals that publish social science research in the business field. By searching for journals in specific areas, we have collected a total of 14 journals, as reveal in step 4.
**The third step** was defining search terms. We defined the search terms for the analysis based on the questions identified in the first step. The search terms used in this research were "Structural equation model" and "SEM".
**The fourth step,** we were merging hits from databases. By collecting business research articles from a given area within the publishing period of 2020 -2024, we obtained the 214 number of articles classified by journals as follows:
Journal of Business Administration-(JBA): 16 articles
Journal of Business, Innovation and Sustainability (JBIS): 25 articles
MUT Journal of Business Administration: 15 articles
Journal of Business Administration The Association of Private Higher Education Institutions of Thailand: 35 articles
Economics and Business Administration Journal Thaksin University: 19 articles
Burapha Journal of Business Management: BJBM: 20 articles
Modern Management Journal: 14 articles
Journal of Accountancy and Management: 18 articles
Journal of Management Science, Suratthani Rajabhat University: 4 articles
Journal of Management Science, Chiang Rai Rajabhat University: 9 articles
Songklanakarin Journal of Management Sciences (SJMS): 8 articles
Journal of Modern Management Science (JMMS): 8 articles
Journal of Arts Management: 15 articles
Journal of Applied Economics and Management Strategy: 8 articles
Following the retrieval of articles that satisfied all inclusion criteria outlined in step 4, we proceeded with the subsequent stages (steps 5-7) of the systematic literature review process. The detailed findings of these steps are presented in the following section.

## RESEARCH RESULTS

A total of 214 articles obtained from 14 journals were classified into SEM categories, in Table 1.

**Table 1** Number of articles classified by type of SEM and year of publication

| Journal | Year | 2020 | | 2021 | | 2022 | | 2023 | | 2024* | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | SEM | | SEM | | SEM | | SEM | | SEM | |
| | No | CB | VB | CB | VB | CB | VB | CB | VB | CB | VB |
| JBA | 16 | 2 | 1 | 4 | 0 | 2 | 1 | 4 | 0 | 2 | 0 |
| JBIS | 25 | 4 | 0 | 2 | 0 | 1 | 1 | 10 | 3 | 4 | 0 |
| MUTJA | 15 | 2 | 0 | 4 | 1 | 0 | 2 | 5 | 1 | 0 | 0 |
| JBAAPHEIT | 35 | 4 | 0 | 12 | 2 | 7 | 1 | 6 | 0 | 3 | 0 |
| EBAJTU | 19 | 2 | 1 | 0 | 2 | 5 | 4 | 3 | 0 | 1 | 1 |
| BJBM | 20 | 0 | 0 | 1 | 0 | 2 | 3 | 8 | 0 | 6 | 0 |
| MMJ | 14 | 3 | 0 | 2 | 0 | 6 | 0 | 3 | 0 | 0 | 0 |
| JAM | 18 | 3 | 1 | 1 | 1 | 7 | 0 | 3 | 0 | 2 | 0 |
| JMSSRU | 4 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 |
| JMSCRRU | 9 | 2 | 0 | 2 | 0 | 4 | 0 | 1 | 0 | 0 | 0 |
| SJMS | 8 | 2 | 1 | 0 | 1 | 2 | 0 | 2 | 0 | 0 | 0 |
| JMMS | 8 | 3 | 0 | 1 | 0 | 2 | 0 | 2 | 0 | 0 | 0 |
| JAM | 15 | 0 | 0 | 3 | 1 | 5 | 0 | 4 | 0 | 2 | 0 |
| JAEMS | 8 | 3 | 0 | 2 | 0 | 2 | 0 | 1 | 0 | 0 | 0 |
| **Total** | **214** | **31** | **4** | **34** | **8** | **46** | **12** | **53** | **5** | **20** | **1** |

***Jan-Mar**

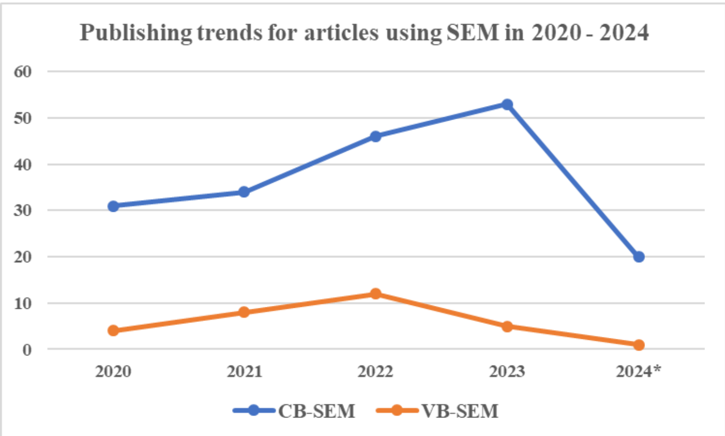


**Figure 1** Publishing trends for articles using SEM in 2020-2024

Data from Table 1 were employed to analyze the publication trends of articles utilizing CB-SEM and VB-SEM in business research from 2020 to 2024. As depicted in Figure 1, data for 2024 were excluded due to the limited timeframe (January-March) represented. This analysis reveals a consistent pattern over the period 2020-2022, where the number of articles employing CB-SEM outpaced those utilizing VB-SEM across all years examined. Furthermore, a projected upward trend is observable in the use of CB-SEM from 2020 to 2023. Conversely, VB-SEM publications exhibit a potential increase from 2020 to 2022, followed by a possible decline beyond that point.

**Table 2** Number and percentage of variables role in the SEM

| Variable in Model | No | % |
|---|---|---|
| Mediating | 166 | 77.57 |
| Moderating | 11 | 5.14 |
| Both Mediating and Moderating | 12 | 5.61 |
| Other (Independent variable in Regression model) | 25 | 11.68 |
| **Total** | **214** | **100** |

Our analysis of causal variable roles within the research models revealed a dominance of mediating variables, as table 2. The majority (83.18%, n = 178) of the business research articles examined employed models primarily comprised of mediating variables. Notably, a substantial portion (77.57%, n = 166) of these models exclusively utilized mediating variables. The inclusion of both mediating and moderating variables within the same model was observed in a smaller subset of articles (5.61%, n = 12). Finally, a minimal number of articles (5.14%, n = 11) presented models solely comprised of moderating variables.
As previously mentioned, SEM analysis comprises two distinct components: a measurement model and a structural model. Notably, SEMs incorporating mediating variables can account for exogenous variables exerting both direct and indirect effects on the research model's outcome variables. However, a recent synthesis of 178 business research articles employing mediating variables revealed a concerning trend. Nearly half (49.4%, n = 88) failed to report the statistical significance of the indirect effects, solely focusing on the direct effects' significance. Conversely, the remaining articles (50.6%, n = 90) appropriately addressed both the direct and indirect influence of exogenous variables on the final variable through the mediating variables within the model. As shown in figure 2.

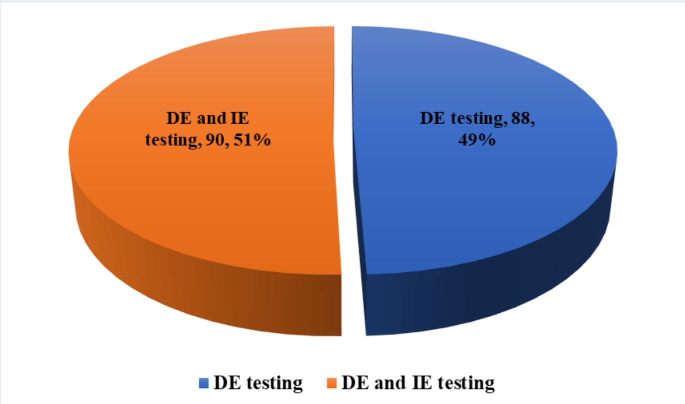


**Figure 2** The proportion of reporting the statistical significance of the influence of external variables on the dependent variable in business research articles.

A key advantage of SEM lies in its ability to construct intricate research models encompassing both measurement and structural components. The structural model often draws upon regression analysis techniques. However, a critical assumption of regression is the absence of significant multicollinearity among independent variables. High correlations between these variables can obscure the true magnitude and direction of their effects on the dependent variable, ultimately leading to spurious conclusions. While regression analysis typically employs VIF and/or tolerance values to assess multicollinearity, SEM offers well-established methods for evaluating the lack of correlation between MM within the same equation. These methods include the AVE-SV and the heterotrait-monotrait (HTMT) ratio approaches.
A recent review of 178 business research articles employing mediating variables revealed a concerning trend. Only 62 articles (34.83%) reported the assessment of discriminant validity using AVE-SV and/or HTMT methods. This finding underscores the necessity for more rigorous evaluations of discriminant validity in SEM applications to ensure the robustness of research conclusions. Furthermore, the systematic review of 214 business research articles identified that construct validity assessment was reported in only 122 articles (57.01%), suggesting a potential shortcoming in current reporting practices. As shown in table 3.

**Table 3** Number and percentage of Construct validity and Discriminant validity reporting

| Reporting | Yes | No | Total |
|---|---|---|---|
| Construct validity (factor loadings, composite reliability, average variance extracted, etc.,) | 122 (57.01%) | 92 (42.09%) | **214** |
| Discriminant validity (AVE-SV, HTMT, etc.,) | 62 (34.83%) | 116 (65.17%) | **178** |

Building upon the findings presented in Table 3, a further analysis is conducted to examine the distribution of business research articles (2020-2024) lacking construct and discriminant validity reporting across different SEM types. Table 4 disaggregates this data by SEM methodology.
The results of the analysis, shown in Table 4, reveal that Business research articles using CB-SEM had a significantly higher propensity for omitting assessments of both construct and discriminant validity compared to those utilizing VB-SEM.

**Table 4** Number and percentage of not reporting about Construct validity and Discriminant validity classified by type of SEM

| Not Reporting | CB-SEM | VB-SEM | Total |
|---|---|---|---|
| Construct validity (factor loadings, composite reliability, average variance extracted, etc.,) | 89 (96.74%) | 3 (3.26%) | **92** |
| Discriminant validity (AVE-SV, HTMT, etc.,) | 107 (92.24%) | 9 (7.76%) | **116** |

Figure 3 depicts the prevalence of concerning measurement characteristics in business research articles. The figure examines the proportion of articles exhibiting: 1) correlation directions contradicting the research hypothesis, 2) modification indices suggesting model misspecification, and 3) standardized parameter estimates exceeding an absolute value of 1.00. Notably, these characteristics were identified in articles that did not report assessments of construct and discriminant validity. All of this happens with business research articles that use CB-SEM.


**Figure 3** The highlights several issues with parameter estimation using CB-SEM

Figure 3 highlights several issues with parameter estimation using CB-SEM. The most frequent discrepancy (47.73%) involved adjustment indices indicative of misspecification in the hypothesized model. Additionally, in 39.64% of instances, the estimated direction of the relationship between variables contradicted the research hypotheses. Finally, exceeding a threshold of 1.00 in standardized parameter estimates, suggestive of unlikely results, was observed in 13.64% of the cases.

# DISCUSSION & CONCLUSION

## Conclusion

This study examines the use of VB-SEM and CB-SEM in business research articles. Key trends emerged: A growing preference for CB-SEM was observed, while VB-SEM usage declined. Most studies (77.57%) employed complex models with latent variables (measured by constructs) and mediating variables. Moderating variables were less prevalent (5.14%), and even fewer studies (5.61%) integrated both. Among studies with mediating variables, only half reported results for both direct and indirect effects. A significant portion lacked proper validity assessment. Discriminant validity was unreported in 65.17% of studies, and construct validity in 42.09%, with these issues more prevalent in CB-SEM articles. Some studies presented findings contradicting initial hypotheses (39.64%), had standardized parameter values exceeding 1.00 (13.64%), or employed model modifications deviating from statistical assumptions (47.73%).

## Discussion

An initial analysis revealed a tendency for business research to favor covariance-based structural equation modeling (CB-SEM) over variance-based structural equation modeling (VB-SEM). This inclination might be attributable to the emphasis placed on theoretical frameworks in business research published within standardized journals. Such frameworks are crucial for developing research models, aligning with the core principle of CB-SEM. CB-SEM utilizes the maximum likelihood approach, which prioritizes testing and comparing the congruence between theory-driven models and empirical data (Hair et al., 2018; Kline, 2023). This process ensures that the model's underlying assumptions are consistent with the observed data. Any theoretical model can be evaluated for this kind of fitness with available empirical data.

SEM excels at explaining multiple statistical relationships simultaneously. This technique allows researchers to visualize and validate complex models, making them easier to understand (Hair et al., 2017, 2018; Kline, 2023). In business research, where human behavior is a key focus, SEM is a crucial tool. It goes beyond analyzing just independent and dependent variables. SEM facilitates the incorporation of mediating variables, which act as intermediaries in the relationship, and controlled variables (moderators) held constant to isolate specific effects.

SEM analysis hinges on a complex theoretical model validated through data. Model complexity and the chosen estimation method (Hayes et al., 2017) necessitate evaluating two distinct models: the measurement model and the structural model (Schumacker & Lomax, 2010; Hair et al., 2010).

The measurement model assesses construct validity (i.e., do measures reflect the intended constructs?) and discriminant validity (i.e., are constructs distinct?) (Ingard, 2023). This study identifies potential model inconsistencies and inaccuracies arising from inadequate discriminant validity in construct measurement. A review of research articles revealed a lack of reporting on construct and discriminant validity, particularly when categorized by SEM type. This highlights the need for renewed focus on discriminant validity to ensure robust and theoretically sound models in SEM research.

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