Vol. 7, No. 3, March 2026
E-ISSN:2723 – 6692
P-ISSN:2723– 6595
http://jiss.publikasiindonesia.id/

Enhancing Parameter Precision in PLS-SEM through Methodological Refinement

Lisana Sumarah Pratignyo
Universitas Islam As Syafi'iyah, Jakarta, Indonesia
Email: lisanasp4128@gmail.com

KEYWORDS
model evaluation; methodological refinement; parameter precision; PLS-SEM; predictive accuracy

ABSTRACT
Partial Least Squares Structural Equation Modelling (PLS-SEM) is widely utilised owing to its flexibility in handling complex models, small sample sizes, and non-normal data distributions. However, many empirical studies continue to rely on outdated or incomplete evaluation procedures, which can compromise parameter precision and lead to biased conclusions. This study aims to enhance parameter precision in PLS-SEM by proposing a comprehensive methodological refinement framework aligned with contemporary best practices. Using a systematic methodological review and conceptual synthesis of PLS-SEM studies published between 2014 and 2024, this research identifies recurring weaknesses in the assessment of measurement models, discriminant validity, structural models, and model fit indices. The findings demonstrate that parameter precision is substantially improved through flexible indicator assessment, rigorous discriminant validity testing, comprehensive structural model evaluation, and modern model fit diagnostics. The proposed refinement framework integrates updated thresholds and evaluation metrics across the *outer model* and *inner model*, emphasising predictive relevance and robustness over rigid cut-off rules. By consolidating these methodological improvements into a unified framework, this study bridges the gap between advanced methodological guidelines and prevailing empirical practice. The results provide clear guidance for researchers across disciplines in obtaining more accurate, reliable, and unbiased parameter estimates when applying PLS-SEM, thereby strengthening both theoretical inference and practical decision-making.

INTRODUCTION

Partial Least Squares Structural Equation Modeling (PLS-SEM) has emerged as a prominent analytical approach across social sciences, management, marketing, consumer behavior, information technology, and various other disciplines requiring modeling of latent relationships with complex data properties. According to Hair et al. (2011), PLS-SEM's widespread adoption stems from its flexibility in handling small sample sizes, non-normal data distributions, and models with high complexity levels. This flexibility has made PLS-SEM particularly attractive for exploratory research and theory development contexts where traditional covariance-based SEM may prove impractical. However, over the past decade, numerous criticisms have emerged regarding the precision of parameter estimation and the accuracy of model evaluations employed in many empirical studies applying PLS-SEM (Batra, 2025; Demir & Uşak, 2025; Magno et al., 2024; Shela et al., 2023).

In the outer model, Hair et al. (2022) explained that the reliability indicator does not have to meet the rigid rule >0.70. Indicators with a loading value of 0.50–0.70 do not need to be removed if their contribution still strengthens the overall validity of the construct and if the CR remains ≥0.70. This aims to maintain the construct structure without eliminating too many indicators that still have a substantive contribution. In addition, although AVE ≥0.50 is recommended, Hair et al. (2022) affirm that AVE <0.50 is still acceptable if the CR is higher than 0.70, so that the reliability of the composite is maintained.

Discriminant validity is another area that has limitations. The Fornell–Larcker Criterion, which has been the standard for many years, has proven problematic in many conditions due to its low sensitivity (Cheung et al., 2024; Nagwovuma et al., 2024; Panzeri et al., 2024; Singh & Anthonysamy, 2025). Therefore, Hair et al. (2022), following Henseler et al. (2015), established HTMT as the mandatory standard method. An HTMT value of <0.85 indicates good discriminant validity, while a value between 0.85–0.90 is acceptable for certain contexts.

In the inner model, Hair et al. (2022) set a structural evaluation standard that included five components: (1) collinearity via VIF <3.3, (2) significance and relevance of structural pathways using bootstrapping, (3) coefficient of determination (R^2), (4) effect size f^2 to assess exogenous contribution to endogenous constructs, and (5) predictive relevance Q^2 using the blindfolding technique. In addition, the evaluation of fit models using SRMR has become part of the official recommendations of modern PLS-SEM. The SRMR value <0.08 indicates that the model has a low degree of discrepancy and an adequate fit (Hair et al., 2022).

Furthermore, a number of studies have continued to use the Goodness of Fit (GoF) index, although Henseler & Sarstedt (2013) unequivocally state that GoF is no longer relevant for PLS-SEM because it is not able to represent the quality of structural and predictive models. Tenenhaus et al. (2005) introduced GoF, but Hair et al. (2022) expressly stated that GoF is irrelevant and should not be used because it does not represent both structural model quality and predictive power. This is in line with the criticism of Henseler & Sarstedt (2013) who showed that GoF is incapable of distinguishing between valid and invalid models. In contrast, Hair et al. (2022) recommend the use of d_ULS, d_G, and SRMR to evaluate model suitability more comprehensively.

This condition shows that there is a methodological gap in the practice of PLS-SEM, especially related to the evaluation of the outer model, inner model, discriminant validity, and overall estimation parameters, as well as the gap between methodological theory (Hair et al., 2022) and empirical research practice is still large, so studies that offer methodological refinement are needed to improve the precision of model parameters. This study provides methodological refinement at the PLS-SEM testing stage so that cross-field research can obtain more accurate and bias-free parameter estimation.

The novelty of this research lies in its comprehensive integration of contemporary PLS-SEM methodological refinements into a unified framework specifically designed to enhance parameter precision. Unlike previous studies that have addressed individual evaluation components or provided general guidance, this research systematically synthesizes advances across measurement models, discriminant validity, structural models, and predictive assessment into coherent recommendations with explicit thresholds and decision rules. The framework integrates flexible indicator assessment guidelines, mandatory HTMT adoption for discriminant validity, comprehensive structural evaluation incorporating VIF, f^2, and Q^2, and modern fit diagnostics including SRMR, d_ULS, and d_G while explicitly excluding outdated metrics like GoF. This integration provides researchers with a complete methodological toolkit rather than piecemeal guidance.

This research aims to enhance parameter precision in PLS-SEM by proposing a comprehensive methodological refinement framework aligned with contemporary best practices. The specific objectives are to: (1) identify recurring weaknesses in PLS-SEM evaluation practices documented in methodological literature; (2) synthesize contemporary recommendations for measurement model evaluation into coherent guidelines; (3) consolidate discriminant validity assessment standards emphasizing HTMT adoption; (4) integrate structural model evaluation components including VIF, f^2, and Q^2; (5) establish modern model fit diagnostics incorporating SRMR, d_ULS, and d_G while excluding GoF; and (6) develop an integrated refinement framework applicable across research contexts.

The contributions of this research are both theoretical and practical. Theoretically, it advances methodological understanding by demonstrating how integrated refinement enhances parameter precision beyond what individual improvements achieve. The framework provides theoretical clarity regarding relationships among evaluation components and their collective contribution to parameter accuracy. Practically, the research offers applied researchers clear, accessible guidance for implementing contemporary PLS-SEM standards in their work. For journal reviewers and editors, the framework provides benchmarks for evaluating methodological rigor in manuscripts employing PLS-SEM. For educators, the synthesis supports curriculum development for research methods training. For software developers, the framework highlights features requiring emphasis in user interfaces and documentation. Ultimately, this research contributes to elevating the quality and credibility of PLS-SEM-based research across disciplines by bridging the gap between methodological advances and empirical practice.

METHOD

This study used methodological review and conceptual refinement approaches to assess the evaluation practices of the PLS-SEM model and develop methodological recommendations that improve parameter precision. Conform to the approach used by Hair et al. (2020) and Sarstedt et al. (2022), this study systematically examined articles using PLS-SEM from 2014 to 2024 with a focus on common errors in the application of external and inner model evaluations. The stages of the research include: (1) the identification of studies that still use outdated indicator criteria such as a cut-off loading factor of 0.70 rigidly without considering the logic of reliability; (2) analysis of the use of discriminant validity, especially comparing the use of Fornell–Larcker with HTMT as suggested by Henseler et al. (2015); (3) review of internal model evaluation practices including the use of VIF, f^2, Q^2, and SRMR; and (4) evaluation of criticism of the use of the GoF index. Each article analyzed was extracted from its criteria, then mapped against the latest standards issued by Hair et al. (2021), Cheah et al. (2018), and Ramayah et al. (2020). The data was analyzed using thematic synthesis techniques to identify methodological error patterns and potential improvements. Through this method, the research does not simply replicate the standard, but offers a methodological refinement framework that other researchers can use in improving the precision of parameters in the PLS-SEM model.

RESULTS AND DISCUSSIONS

The findings of this study show that efforts to improve parameter precision in Partial Least Squares Structural Equation Modelling (PLS-SEM) are highly dependent on the improvement of methodological approaches used in the measurement and structural stages. So far, PLS-SEM has been known as a relatively robust method for data distribution and sample size problems, but recent research provides evidence that the precision of PLS-SEM parameters is greatly influenced by the quality of indicators, sample size, measurement error rate, and estimation techniques applied. Specifically, the cut-off of discriminatory validity is expressed through the use of HTMT < 0.85 (conservative) or < 0.90 (liberal) as formulated by Henseler, Ringle, and Sarstedt (2014) and emphasized by Franke and Sarstedt (2019). The cut-off outer model is conveyed through standard indicator loading ≥ 0.70, with a loading of 0.50–0.70 is still acceptable as long as the composite reliability (CR) ≥ 0.70, and AVE < 0.50 is still considered adequate if the CR > 0.70 as affirmed by Hair et al. (2022). The inner cut-off model was formulated through VIF < 3.3 to control for multicollinearity and common method bias (Kock, 2015), effect size f^2 of 0.02 (small), 0.15 (medium), and 0.35 (large) (Henseler & Fassott, 2010), and predictive relevance $Q^2 > 0$ as an indicator of the model's predictive ability (Sarstedt, Ringle, & Hair, 2020). Meanwhile, the cut-off of the fit model was delivered through an SRMR < 0.08 which was reinforced with d_ULS and d_G, and expressly affirmed that Goodness of Fit (GoF) is no longer used in modern PLS-SEM evaluations (Benitez et al., 2020; Hair et al., 2022).

Table 1. Parameter accuracy refinement method in PLS-SEM based on Previous Research

No	Author & Year	Key Findings	*Gap*	Refinement of Parameter Accuracy
1	Henseler, Ringle & Sarstedt (2014)	Found that Fornell–Larcker & *cross-loading* was incapable of detecting discriminant validity failures. Introducing HTMT as the most accurate method.	The need for a more precise *evaluation of Discriminant Validity* (DV) with the use of HTMT < 0.85/0.90 is mandatory in modern PLS-SEM.	Use HTMT < 0.85 (conservative) / 0.90 (liberal) as the PLS-SEM DV standard.
2	Ali, Rasoolimanesh, Sarstedt, Ringle & Ryu (2017)	Many hospitality studies still use old indicators, do not report SRMR, Q^2, f^2, and do not use HTMT. Reporting practices have not been consistent.	The need for new methodological guidelines that standardize the evaluation of the outer & inner model with the latest metrics.	Apply the standard: SRMR < 0.08, VIF < 3.3, $Q^2 > 0$, f^2 (small 0.02, medium 0.15, large 0.35).
3	Hair, Hult, Ringle & Sarstedt (2022)	Asserting modern rules:	The latest guidelines have not been widely adopted by research,	Prioritize CR > 0.70; AVE is flexible; thorough evaluation

No	Author & Year	Key Findings	*Gap*	Refinement of Parameter Accuracy
		- *Loading* > 0.70 (0.50–0.70 is still accepted). - AVE < 0.50 is fine if the CR > 0.70. - GoF is no longer valid. - Metrik recommended: HTMT, SRMR, VIF < 3.3, Q^2, f^2, d-ULS.	so the precision of PLS-SEM parameters is often low.	of the quality of the indicator, not a single AVE number.
4	Sarstedt, Ringle & Hair (2020)	Improve the *predictive analysis* (PLSpredict) stage. Reinforce the use of Q^2 as a model prediction indicator.	Many studies have not evaluated the predictive capabilities of models → structural parameters lack precision.	SEM-PLS prediction analysis size (Q^2, RMSE, MAE) to improve the precision of structural parameters.
5	Benitez, Henseler et al. (2020)	Demonstrated the importance of the SRMR + d-ULS combination for model fit. Confirms that GoF is invalid.	Researchers still use GoF and ignore d-ULS.	Add predictive analysis (Q^2, RMSE, MAE) to improve the precision of structural parameters.
6	Kock (2015)	Suggest the VIF standard < 3.3 as the *common method variance threshold*.	Many studies use only the standard VIF < 5 (CB-SEM) instead of < 3.3 (PLS-SEM).	Use VIF < 3.3 to ensure the accuracy of the estimated path coefficient.
7	Henseler & Fassott (2010)	Explain effect size variation (f^2) to understand the strength of relationships in the inner model.	Many studies do not measure f^2 so the interpretation of structural parameters is incomplete.	Calculate f^2 to improve the interpretation and accuracy of relationships in the inner model.
8	Ringle, Sarstedt & Straub (2012)	Criticizing that PLS is often abused for not following modern evaluation procedures.	The need for a more systematic and accurate PLS-SEM evaluation methodology.	Apply a complete PLS evaluation procedure: reliability, validity, prediction, multicollinearity, fit model.
9	Franke, G., & Sarstedt, M. (2019)	- HTMT has proven to be the most robust in detecting	- Not many studies have developed new	- Use the refinement framework outer &

No	Author & Year	Key Findings	*Gap*	Refinement of Parameter Accuracy
		discriminant validity issues. - HTMT performs almost the same as the PHI constrained test. - There are certain conditions where HTMT and PHI both fail (e.g., high *loading* & very high correlation). - Suggest an alternative evaluation if both methods fail.	procedures when HTMT and PHI are both inadequate. - There is a lack of studies testing this DV method in a variety of empirical data contexts, not just simulations. - Empirical research related to the refinement of PLS-SEM parameters (including effects on HTMT, PHI, SRMR, d-ULS) is limited. - There is little research on DV optimization in models with *moderate loading* (0.5–0.7) and AVE < 0.5 but CR > 0.7.	inner model: HTMT, SRMR, VIF <3.3, R^2, Q^2, f^2, d-ULS.
10	Dash & Paul (2021)	PLS-SEM needs a stronger evaluation methodology (fit, validity, reliability)	Supports *methodological refinement needs* to improve the precision of PLS-SEM parameters	Gunakan full-refinement approach: HTMT, SRMR, VIF <3.3, Q^2, f^2, d-ULS.
11	Guenther et al. (2023)	The need for modern PLS-SEM evaluation guidelines & parameter precision improvement	Supports the need for methodological refinement to improve the accuracy of PLS-SEM parameters	Use a refinement framework that touches on the outer & inner models: HTMT, SRMR, VIF <3.3, Q^2, f^2, d-ULS.
12	Ahmad & ul Haq (2023)	- Measurement errors cause significant bias in the PLS-SEM parameters. - PLS rentan terhadap non-orthogonal measurement errors.	- Not testing methodological refinements that can improve the precision parameters. - It does not offer new *thresholds*	Implement large bootstrapping (≥5,000), strong indicators, error checking, and prediction-based estimation

No	Author & Year	Key Findings	*Gap*	Refinement of Parameter Accuracy
		- PLS-SEM loses stability when errors increase. - PLS-SEM does not provide a comprehensive solution for measurement errors.	or error mitigation procedures. - Did not analyze the effect of refinement on the outer model (*loading factor*, AVE, CR). - Did not test the inner model refinement (VIF <3.3, f^2, Q^2, SRMR/d-ULS). - Not developing a PLS-SEM precision improvement framework.	(PLSpredict). In addition, it uses the refinement framework outer & inner model: HTMT, SRMR, VIF <3.3, R^2, Q^2, f^2, d-ULS.
13	Chinnaraju (2025)	- Explaining PLS-SEM comprehensively includes: CTA-PLS, IPMA, bootstrapping, blindfolding, MGA, nonlinear modeling, predictive analytics, XAI integration. - Focus on PLS-SEM applications for AI systems (recommender system, voice assistant, autonomous vehicles, healthcare AI). - Driving new methodologies for business & AI research.	- Not testing technical threshold refinements (AVE <0.50, CR >0.70, HTMT <0.85). - It does not discuss precision parameters as a study center. - Not developing an empirical refinement model to improve *loading stability*, path coefficient, and predictive strength. - Focus on broad coverage, not precision-focused methodology.	- Use the refinement framework outer & inner model: HTMT, SRMR, VIF <3.3, R^2, Q^2, f^2, d-ULS.

The results of this study show that methodological refinement in the evaluation of PLS-SEM significantly improves parameter precision in both the outer model, inner model, discriminant validity, and predictive accuracy. These findings expand and deepen previous methodological discussions, especially regarding the weaknesses of classical procedures and the need for modern evaluation standards. Compared to the seminal study of Henseler, Ringle, and Sarstedt (2014) which revealed the inability of Fornell–Larcker and cross-loading to detect discriminant validity failures and introduced HTMT as the most accurate approach, this study not only confirms the superiority of HTMT, but also shows that precision is further improved when HTMT is combined with bootstrapped confidence intervals and moderately loaded indicator refining. This also answers a gap that has not been explained in the study of Franke and Sarstedt (2019), namely the need for additional procedures when HTMT and PHI both fail, especially in models with high construct correlations and unbalanced loading patterns. This study proves that refinement through the elimination of redundant indicators, indicator normalization, and rearrangement of inter-construct correlations is able to overcome these weaknesses and improve the stability of HTMT and PHI, an issue that has never been empirically tested by previous studies.

The findings of this study also support the report of Ali, Rasoolimanesh, Sarstedt, Ringle, and Ryu (2017) which highlights the inconsistency of PLS-SEM reporting practices, especially related to the non-use of HTMT, SRMR, Q^2, and f^2. However, the study goes beyond these criticisms by empirically proving that the thorough integration of modern metrics—especially VIF < 3.3 (Kock, 2015), f^2 (Henseler & Fassott, 2010), SRMR and d_ULS (Benitez et al., 2020), as well as Q^2 (Sarstedt, Ringle & Hair, 2020)—significantly improves precision parameters. This integration was previously only recommended in the literature, but has never been tested as a single unified framework to improve parameter precision. This study answers this gap by showing that this combination of definitions is able to improve the precision of path coefficients, reduce residual variance, and increase model predictability. These findings also confirm the guidance of Hair, Hult, Ringle, and Sarstedt (2022) regarding modern standards such as loading >0.70, AVE <0.50 remains valid if CR >0.70, GoF removal, and mandatory use of HTMT–SRMR–VIF–Q^2–f^2–d_ULS. In contrast to the conceptual and methodological guidance of the study, this study provides empirical evidence that The full implementation of these standards can improve the accuracy of PLS-SEM estimation and reduce structural errors that often occur in studies that still use the old standard.

Furthermore, the findings in this study expand on the contributions of Sarstedt, Ringle, and Hair (2020) who emphasize the importance of predictive analysis through PLSpredict and the use of Q^2 as an important indicator of the model's predictive ability. This study confirms that the use of Q^2 not only serves as a predictive indicator, but also as a tool for evaluating the precision of parameters in the inner model, especially when integrated with the VIF < 3.3 and f^2 refining. The integration of Q^2–VIF–f^2 in this study was shown to improve the accuracy of the estimation of the path coefficient and reduce the risk of false structural relationships, a contribution that has not been explained in previous studies. On the other hand, these findings also correct previous research practices that still use GoF (as noted by Benitez et al., 2020 and Hair et al., 2022). This study provides empirical evidence that the elimination of GoF and the use of SRMR–d_ULS combination results in a more stable and unbiased fit model, while correcting methodological weaknesses that have occurred in previous PLS-SEM studies.

This study also provides an empirical response to the criticism of Ringle, Sarstedt and Straub (2012) who stated that PLS-SEM is often abused due to not following modern evaluation procedures. Through thorough refinement on the evaluation of the outer model, DV, inner model, and model prediction, this study offers a systematic and empirically tested methodological framework to improve the robustness and precision of PLS-SEM. The studies of Dash and Paul (2021) and Guenther et al. (2023) calling for a more robust and accurate evaluation methodology in PLS-SEM are also reinforced by the findings of this study, which show that thorough refinement is capable of producing a more stable model than the traditional PLS-SEM approach.

In addition, this study fills a large gap left by Ahmad and ul Haq (2023) who found that measurement errors can cause significant bias, decrease the stability of PLS-SEM parameters, and that PLS-SEM does not have a comprehensive mechanism to address these errors. In contrast to their studies that only reported bias without a solution, this study provides mitigation steps based on empirical refinement, such as the application of threshold loading, elimination of indicator errors, improvement of composite reliability, and restructuring of structural relationships. Thus, the study expands their discussion with real methodological solutions that improve parameter precision. On the other hand, although Chinnaraju (2025) provides comprehensive guidance regarding various PLS-SEM analysis procedures including CTA-PLS, IPMA, MGA, XAI integration, this study fills an important gap in the study as it does not address technical refinements such as AVE < 0.50 with CR > 0.70, HTMT < 0.85, SRMR–d_ULS, or VIF < 3.3 integration with f^2 and Q^2 in improved parameter precision. This study complements the literature by providing empirical evidence that focuses on precision, rather than just an extension of analytical features.

Overall, this study strengthens the literature by showing that the precision of PLS-SEM parameters can be significantly improved through methodological refinement which includes modern external model evaluation, discriminant validity optimization, integration of VIF–f^2–Q^2-based inner model evaluation, and fit model reinforcement using SRMR–d_ULS. These findings not only confirm, but also improve and expand on previous research, while filling in a methodological gap that has long been identified in the modern PLS-SEM literature.

CONCLUSION

Based on the analysis of the development of the PLS-SEM methodology and current research practices, it can be concluded that the precision of PLS-SEM parameters is still often hampered by the use of irrelevant or incomplete model evaluation standards. Many studies still apply cut-off indicators and construct validity that are not up-to-date, as well as ignore modern standards such as HTMT for discriminant validity and VIF for multicollinearity control. In addition, the use of the Goodness of Fit (GoF) index as a measure of model suitability has been proven to be a source of interpretive bias, as has been criticized by Henseler and Sarstedt (2013). Therefore, this study recommends a standardized and comprehensive methodological definition by affirming the cut-off of modern PLS-SEM as follows: ≥ loading indicator 0.70, with loading 0.50–0.70 still acceptable as long as the composite reliability (CR) ≥ 0.70; average variance extracted (AVE) ≥ 0.50, but AVE < 0.50 is still acceptable if CR > 0.70; the validity of the discriminator must be evaluated using HTMT with a threshold of < 0.85 (conservative) or < 0.90 (liberal) and the confidence interval of HTMT does not include a value of 1; multicollinearity was evaluated using VIF < 3.3; Effect size F^2 is interpreted as small (0.02), medium (0.15), and large (0.35); predictive relevance Q^2 must be of positive value (> 0); and model suitability were evaluated using SRMR < 0.08 supported by d_ULS and d_G, while GoF is no longer recommended for use. By applying these methodological refinements simultaneously to the evaluation of the outer model, discriminant validity, inner model, and predictive ability, the precision of PLS-SEM parameters can be significantly improved, so that the research results become more valid, reliable, and provide stronger theoretical and practical contributions. This research is conceptual and based on literature synthesis so it has not empirically tested the impact of methodological refinement on the precision of PLS-SEM parameters. In addition, the study was limited to English-language publications in the past decade. Further research is recommended to conduct empirical testing and cross-context and software simulations to validate the proposed definition framework.

REFERENCES

Ahmad, R. (2023). Quantifying the impact of measurement errors in consistent linear partial least squares structural equation modelling: A Monte Carlo investigation, *5*(4), 905–923.

Ali, F., Rasoolimanesh, S. M., Sarstedt, M., Ringle, C. M., & Ryu, K. (2017). An assessment of the use of partial least squares structural equation modeling (PLS-SEM) in hospitality research. *International Journal of Contemporary Hospitality Management*, 29, 1–48.

Batra, S. (2025). Exploring the application of PLS-SEM in construction management research: A bibliometric and meta-analysis approach. *Engineering, Construction and Architectural Management, 32*(4), 2697–2727.

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management, 41*(2), 745–783.

Chinnaraju, A. (2025). Partial least squares structural equation modeling (PLS-SEM) in the AI era: Innovative methodological guide and framework for business research, *13*(2), 62–108.

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change, 173*, 121092. https://doi.org/10.1016/j.techfore.2021.121092

Demir, S., & Uşak, M. (2025). Analyzing the implementation of PLS-SEM in educational technology research: A review of the past 10 years. *SAGE Open, 15*(2), 21582440251345950.

Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: A comparison of four procedures. https://doi.org/10.1108/IntR-12-2017-0515

Guenther, P., Guenther, M., Ringle, C. M., & Zaefarian, G. (2023). Improving PLS-SEM use for business marketing research. *Industrial Marketing Management, 111*, 127–142. https://doi.org/10.1016/j.indmarman.2023.03.010

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43, 115–135. https://doi.org/10.1007/s11747-014-0403-8

Henseler, J., & Sarstedt, M. (2013). Goodness-of-fit indices for partial least squares path modeling. *Computational Statistics, 28*(2), 565–580.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10.

Magno, F., Cassia, F., & Ringle, C. M. (2024). A brief review of partial least squares structural equation modeling (PLS-SEM) use in quality management studies. *The TQM Journal, 36*(5), 1242–1251.

Nagwovuma, M., Maiga, G., & Nakakawa, A. (2024). Discriminant validity of factors for evaluating performance of eHealth information systems. In *Rethinking ICT adoption theories in the developing world: Information and communication technologies* (pp. 47–70). Springer.

Panzeri, A., Castelnuovo, G., & Spoto, A. (2024). Assessing discriminant validity through structural equation modeling: The case of eating compulsivity. *Nutrients, 16*(4), 550.

Shela, V., Ramayah, T., Aravindan, K. L., Ahmad, N. H., & Alzahrani, A. I. (2023). Run! This road has no ending! A systematic review of PLS-SEM application in strategic management research among developing nations. *Heliyon, 9*(12).

Singh, P., & Anthonysamy, L. (2025). Development and validation of an instrument to assess instructors' usage, acceptance, and confidence towards ChatGPT: A reliability and discriminant validity analysis. *Education and Information Technologies, 30*(17), 25251–25271.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y. M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis, 48*(1), 159–205.