A Systematic Review of Structural Equation Modeling Practices in Engineering Education

VINCENT OLUWASETO FAKIYESI, University of Georgia

Vincent Oluwaseto Fakiyesi is a doctoral student in the Engineering Education program at the University of Georgia. He holds a bachelor's degree in Chemical Engineering and is interested in advancing assessment practices to better understand student learning. His research focuses on cognitive diagnostic modeling, student misconceptions, and adaptive assessment systems. He applies diagnostic models to analyze large-scale educational assessment data and generate actionable insights that support teaching, learning, and personalized feedback in engineering education. He also examines assessment practices in the era of generative artificial intelligence, emphasizing adaptive, interpretable, and learning-centered systems.

Dr. Nathaniel Hunsu, The University of Georgia

Nathaniel Hunsu is an Associate Professor of Engineering Education at the University of Georgia, affiliated with the Engineering Education Transformational Institute (EETI) and the School of Electrical and Computer Engineering. He leads the Engineering Student Learning and Engagement Research (ESLER) group, mentoring students in projects that explore how engineering learners engage with tasks, technologies, and learning environments. His research focuses on conceptual understanding, epistemic cognition, and student engagement, with an emphasis on evidence-based strategies that enhance learning in engineering education. He applies quantitative research designs, systematic reviews, meta-analysis, and assessment instrument development to advance both the theory and practice of engineering education. Dr. Hunsu's work also investigates the use of emerging educational technologies, including AI, XR, and robotics, in fostering active and self-regulated learning. His goal is to bridge research and practice, equipping educators and learners to achieve meaningful, lasting learning outcomes.

Dr. Olanrewaju Paul Olaogun, Merrimack College

Dr. Olanrewaju Paul Olaogun is an Assistant Instructional Professor of Electrical and Computer Engineering in the Department of Mechanical and Electrical Engineering at Merrimack College. He holds a Ph.D. in Engineering from the University of Georgia, Athens, GA, USA. His research examines the interplay of cognitive, affective, and motivational factors to improve learning outcomes among engineering students. He uses quantitative methods to study learning models and seeks to apply theoretical insights to practical educational interventions. Additionally, he is interested in understanding the role of technology on engineering education, particularly how meaningful learning occurs within virtual reality environments. His research contributions to engineering education have been published in reputable academic journals and international conference proceedings.

ISAAC DAMILARE DUNMOYE, University of Georgia

Isaac Dunmoye PhD in Engineering (in view), University of Georgia, USA, M.Sc. in Electrical Engineering, University of Cape Town, South Africa, 2022. B.Eng. in Agricultural and Biosystems Engineering, University of Ilorin, Nigeria, 2016.

A Systematic Review of Structural Equation Modeling Practices in Engineering Education

Introduction

Structural equation modeling (SEM) is a theory-driven family of statistical techniques that integrates measurement models and structural relationships among latent constructs (Bollen, 1989; Jöreskog, 1973). SEM has been widely adopted in education research because it allows scholars to examine complex relationships among constructs such as motivation, engagement, identity, and self-efficacy while accounting for measurement error (Kline, 2023). As engineering education researchers increasingly seek to test theoretically grounded models of learning and persistence, SEM has become a prominent quantitative method in the field.

Foundational SEM literature emphasizes that valid inference depends not only on acceptable model fit, but also on rigorous measurement practices, transparent reporting, and theoretically justified model specification (Anderson & Gerbing, 1988; Hu & Bentler, 1999). Best-practice guidelines recommend explicit reporting of reliability and validity evidence, appropriate estimation methods, sample adequacy, and theoretically motivated model modifications (Byrne, 2001; Hair et al., 2019). When these practices are not followed, SEM results may appear statistically sound while lacking substantive validity.

In engineering education research, SEM has been used to model a wide range of learning and affective processes, including engineering identity development (Godwin & Kirn, 2020), motivation and persistence (Godwin & Kirn, 2020; Lockhart et al., 2025), learning during internships (Goller et al., 2020), and the psychological costs of pursuing engineering careers (Henderson et al., 2022). While these studies demonstrate the analytic power of SEM, concerns remain regarding the consistency, transparency, and rigor with which SEM is applied and reported in engineering education literature. To date, no systematic methodological review has examined how SEM practices align with established standards within this research community.

Despite extensive methodological guidance in the SEM literature, there remains limited empirical understanding of how these standards are enacted in practice within engineering education research. This study addresses this gap by systematically examining the alignment between recommended SEM practices and their implementation in published engineering education studies.

Purpose and Research Questions

The purpose of this work-in-progress paper is to systematically examine how SEM is applied, validated, and reported in engineering education research. Using a PRISMA-guided systematic review, this paper reports preliminary findings from an in-depth methodological analysis of 20 peer-reviewed engineering education studies employing SEM.

This study addresses the following research questions:

RQ1: What types of SEM approaches (e.g., covariance-based or variance-based) and estimation methods are used in engineering education research?
RQ2: How do engineering education studies report measurement quality, including reliability and validity evidence, when using SEM?
RQ3: To what extent do SEM-based studies justify model fit evaluation and model modification decisions?

Methods

To enhance the reproducibility of the systematic review, we followed the procedures of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Page et al., 2021). This framework offers a well-defined process for carrying out systematic reviews and meta-analyses, and previous research has validated its effectiveness (Power, 2021).

Eligibility Criteria

This systematic review included empirical, peer-reviewed studies that employed structural equation modeling (SEM) or closely related latent variable modeling approaches within the context of engineering education. Eligible studies were required to:
(1) be written in English;
(2) be published between January 2013 and December 2025;
(3) involve undergraduate, graduate, or professional engineering learners or engineering education stakeholders; and
(4) report empirical SEM results, including measurement and/or structural models.

We excluded studies that were nonempirical (e.g., conceptual papers, reviews, meta-analyses), relied solely on observed-variable regression without latent constructs, or did not focus on engineering or engineering education contexts. Duplicate publications and updated versions of previously published studies were also excluded.

Information Sources and Search Strategy

With support from a university librarian, search terms and databases were finalized after reviewing prior methodological reviews in quantitative and engineering education research. Electronic searches were conducted across ERIC (via EBSCO), APA PsycINFO, Engineering Village, Web of Science, ScienceDirect, and Education Research Complete. The search strategy employed combinations of SEM-related terms and domain-specific terms, including *"structural equation modeling," "SEM," "confirmatory factor analysis," "path analysis,"* and *"latent variable modeling,"* combined with *"engineering education."*

The initial search yielded 6,513 records across all databases. Following de-duplication and application of the inclusion criteria, 1,316 unique studies remained. Title and abstract screening was conducted using Rayyan based on the predefined eligibility criteria. Full-text screening is currently ongoing. A PRISMA flow diagram summarizing the search and screening process is provided in the Appendix

Preliminary Sample for Work-in-Progress Analysis

Following abstract screening, 272 studies were identified as explicitly focusing on engineering education and the application of structural equation modeling. Full-text screening is currently underway. However, due to time constraints associated with this work-in-progress submission, we conducted an in-depth methodological analysis of a preliminary subset of 20 peer-reviewed articles that fully met all inclusion criteria. This subset was analyzed to support early identification of dominant SEM practices, reporting patterns, and methodological trends within engineering education research, while full-text screening and coding of the remaining studies continue.

Results

This section reports preliminary findings from full-text methodological coding of 20 peer-reviewed engineering education studies that employed structural equation modeling (SEM). These studies were selected from the 272 engineering-focused articles identified after abstract screening and represent an initial analytic subset used to characterize prevailing SEM practices in the field. The results focus on modeling approach, data characteristics, reliability and validity reporting, model evaluation practices, and use of advanced SEM techniques.

Across all 20 studies, SEM was implemented exclusively using a covariance-based SEM (CB-SEM) framework, typically following a two-step process of confirmatory factor analysis (CFA) and structural model testing. SEM was most commonly used to examine relationships among latent psychosocial and learning-related constructs, including engineering identity, motivation, self-efficacy, belonging, career intentions, and learning experiences. All studies relied on cross-sectional survey data, with sample sizes ranging from approximately 150 to over 1,000 participants, generally meeting recommended thresholds for CB-SEM estimation.

Reporting of internal consistency reliability was nearly universal. Nineteen of the 20 studies reported Cronbach's alpha values for all latent constructs, and all studies reported standardized factor loadings from CFA. However, evidence of construct validity was reported less consistently. Fewer than half of the studies reported average variance extracted (AVE), and only a small subset explicitly addressed discriminant validity through formal criteria. All reviewed studies reported at least one global model fit index, most commonly the comparative fit index (CFI) and the root mean square error of approximation (RMSEA).

Post-hoc model modifications were reported in approximately half of the studies, typically justified using statistical criteria such as modification indices, with limited theoretical grounding. Transparency regarding missing data treatment was limited, with only five studies explicitly reporting their handling approach. Mediation and indirect effects were examined in 18 of the 20 studies. Six studies conducted multigroup analyses, yet only three explicitly tested measurement invariance prior to group comparisons. No study employed longitudinal SEM designs or tested invariance across time.

Overall, these preliminary findings suggest that while SEM is widely adopted in engineering education research for theory-driven modeling, reporting practices related to construct validity, missing data handling, and advanced SEM procedures remain inconsistent.

Discussion

This work-in-progress systematic review provides preliminary insight into how structural equation modeling (SEM) is applied and reported in engineering education research. Analysis of 20 peer-reviewed studies shows that SEM is most often used to examine theoretically grounded relationships among affective, motivational, identity-related, and learning constructs such as self-efficacy, engagement, and persistence. These applications reflect the field's growing interest in modeling complex learning and psychological processes using covariance-based SEM and cross-sectional survey designs, typically

implemented through software such as AMOS and Mplus (Godwin & Kirn, 2020; Goller et al., 2020; Henderson et al., 2022).

Despite the widespread adoption of SEM, the findings reveal inconsistencies in measurement rigor and reporting practices. While nearly all studies reported internal consistency reliability, fewer provided adequate evidence of construct validity, including convergent or discriminant validity indices. In several cases, confirmatory factor analysis was treated primarily as a procedural step rather than a substantive evaluation of measurement quality. This pattern limits confidence in the interpretation of structural relationships, particularly when SEM findings are used to inform instructional design or policy decisions (Al Mamun et al., 2022; Godwin & Kirn, 2020).

A second recurring concern involves post-hoc model modifications introduced to improve fit indices with limited theoretical justification. Although model refinement is an accepted component of SEM, reliance on modification indices without grounding in theory risks shifting analyses from theory testing toward data-driven fitting (Henderson et al., 2022). In contrast, studies that explicitly aligned measurement and structural decisions with established theoretical frameworks such as identity-based motivation or social cognitive theory demonstrated greater coherence and interpretive clarity (Godwin & Kirn, 2020; Lingappa et al., 2020).

Finally, although several studies conducted subgroup analyses related to gender, first-generation status, or disciplinary context, formal tests of measurement invariance were rarely reported. This limitation is particularly consequential given the field's increasing attention to equity and inclusion in engineering education (Verdín, 2025)(. Without establishing invariance, observed group differences may reflect measurement artifacts rather than substantive disparities. Together, these findings suggest that while SEM is now central to engineering education research, greater emphasis is needed on transparent reporting, rigorous measurement validation, and theory-driven modeling decisions.

Conclusion and Future Work

This work-in-progress systematic review offers an initial synthesis of SEM practices in engineering education based on preliminary coding of 20 peer-reviewed studies. The findings indicate that SEM is commonly used to model theoretically grounded relationships among latent constructs, with consistent reporting of model fit and internal consistency reliability. However, construct validity evidence, justification of model modifications, and measurement invariance testing remain inconsistently reported. As full-text screening and coding of the remaining 272 engineering-focused studies continue, the completed review will extend these analyses to examine additional methodological dimensions, including longitudinal modeling, missing data treatment, and alignment between theory and analytic decisions. The long-term goal of this work is to move beyond identifying gaps by offering concrete reporting recommendations and methodological guidance to support more rigorous, transparent, and cumulative SEM research in engineering education.

References

Al Mamun, A., Hossain, A., Salehin, S., Khan, S. H., & Hasan, M. (2022). Engineering students’ readiness for online learning amidst the COVID-19 pandemic. *Educational Technology & Society*, *25*(3), 30–45.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological bulletin*, *103*(3), 411.

Bollen, K. A. (1989). A new incremental fit index for general structural equation models. *Sociological methods & research*, *17*(3), 303–316.

Byrne, B. M. (2001). Structural equation modeling: Perspectives on the present and the future. *International Journal of Testing*, *1*(3-4), 327–334.

Godwin, A., & Kirn, A. (2020). Identity-based motivation: Connections between first-year students' engineering role identities and future-time perspectives. *Journal of Engineering Education*, *109*(3), 362–383.

Goller, M., Harteis, C., Gijbels, D., & Donche, V. (2020). Engineering students' learning during internships: Exploring the explanatory power of the job demands-control-support model. *Journal of Engineering Education*, *109*(2), 307–324.

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.

Henderson, T. S., Shoemaker, K. A., & Lattuca, L. R. (2022). Career calculus: Assessing the psychological cost of pursuing an engineering career. *Journal of Engineering Education*, *111*(4), 770–791.

Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1–55.

Jöreskog, K. G. (1973). Analysis of covariance structures. In *Multivariate analysis–III* (pp. 263–285). Elsevier.

Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford publications.

Lingappa, A. K., Shah, A., & Mathew, A. O. (2020). Academic, family, and peer influence on entrepreneurial intention of engineering students. *Sage Open*, *10*(3), 2158244020933877.

Lockhart, M. E., Rambo-Hernandez, K., & Kwok, O.-M. (2025). Exploring engineering majors’ engineering identities utilizing a traditional identity framework: validity evidence for the new EngID Scale. *European Journal of Engineering Education*, *50*(4), 855–877.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., & Brennan, S. E. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *bmj*, *372*.

Power, J. (2021). Systematic reviews in engineering education: a catalyst for change. *European Journal of Engineering Education*, *46*(6), 1163–1174.

Verdín, D. (2025). Unmasking the Impact of first-generation college students’ psychological capital: A person-centered approach. *Journal of First-generation Student Success*, *5*(2), 140–163.

Appendix A1: Overview of SEM Reporting Practices in the Preliminary Sample (N = 20)

SEM Practice Characteristic	Number of Studies (N = 20)
Covariance-based SEM (CB-SEM)	20
Cross-sectional design	20
Cronbach's α reported	19
CFA reported prior to SEM	20
AVE reported	8
Discriminant validity assessed	6
Post-hoc model modification reported	10
Missing data handling described	5
Mediation / indirect effects tested	18
Multigroup SEM conducted	6
Measurement invariance tested	3
Longitudinal SEM used	0

Appendix A2: A Prisma Flow Diagram.