2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #52663

Beyond Measurement: Mapping the Design and Theory of Adaptive Formative Systems in STEM and 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.

Anthony Fakiyesi, Faktlens Technologies Limited

Anthony Fakiyesi is a cybersecurity professional and researcher with a Master's degree in Cybersecurity and Human Factors from Bournemouth University. His work focuses on the design and analysis of complex digital systems, with particular interest in how data-driven and intelligent systems can be used to support decision-making, learning, and system resilience.

His research interests extend to the intersection of cybersecurity, artificial intelligence, and adaptive systems, particularly in understanding how user behaviour, system feedback, and data analytics can inform the design of responsive and secure digital environments. Drawing from his experience in security monitoring, threat analysis, and human-centred security, he is interested in how adaptive and interpretable systems can be designed to support both technical performance and user understanding.

His broader research direction explores how principles from cybersecurity, such as risk modelling, behavioural analysis, and system feedback loops, can inform the development of adaptive and data-driven systems in domains including education, where personalised feedback and system responsiveness are critical.

WIP: Beyond Measurement: Mapping the Design and Theory of Adaptive Formative Systems in STEM and Engineering Education

1.0 Introduction

Formative assessment is widely recognized as a core mechanism for improving learning rather than merely measuring achievement. In their foundational work, Black and Wiliam [1] define formative assessment as a process in which evidence of student learning is elicited, interpreted, and used to inform instructional decisions that advance learning. This assessment-for-learning perspective emphasizes feedback, learner engagement, and instructional responsiveness, distinguishing formative practices from summative approaches focused on grading and accountability. Subsequent scholarship has reinforced this framing, linking formative assessment to metacognition, self-regulated learning, and conceptual understanding outcomes that are particularly critical in STEM and engineering education, where learning is cumulative and conceptually demanding [2, 3].

In engineering education, formative assessment supports students' development of conceptual understanding, problem-solving skills, and professional judgment by making thinking visible and actionable [4]. However, implementing high-quality formative assessment at scale remains challenging in large enrollment STEM courses. These challenges have motivated increasing interest in technology-enhanced and data-driven approaches that promise timely and personalized feedback.

Parallel to these pedagogical developments, advances in artificial intelligence, psychometrics, and learning analytics have fueled the growth of adaptive learning and assessment systems. Many such systems rely on established models including Item Response Theory (IRT), Computerized Adaptive Testing (CAT), Bayesian knowledge tracing, reinforcement learning, and ELO-based algorithms to personalize item selection or learning pathways [5, 6]. In STEM contexts, adaptivity is often operationalized through dynamic adjustment of item difficulty, sequencing, or mastery thresholds based on learner performance data.

Despite their technical sophistication, recent literature suggests that many adaptive systems prioritize measurement efficiency and prediction accuracy over learning support. Adaptivity is frequently framed in terms of *what comes next* rather than *how feedback supports understanding, reflection, and instructional action*. Qadir et al. [7] highlight this misalignment, arguing that formative assessment is fundamentally "for aiding, not grading." When adaptive systems primarily automate scoring or difficulty adjustment without explicit feedback mechanisms, they risk reproducing summative logics within ostensibly formative technologies.

Reviews in learning analytics further note that adaptive systems often emphasize cognitive performance indicators while offering limited insight into how feedback leads to learning improvement [8]. In engineering education specifically, adaptive tools are frequently introduced as technical solutions with minimal articulation of their pedagogical assumptions or alignment with formative assessment theory. Moreover, affective and behavioral dimensions such as confidence, engagement, and persistence are rarely incorporated into adaptive decision-making, despite evidence that these factors significantly influence learning in STEM domains [9, 10]. Together, foundational formative assessment theory and recent adaptive systems research reveal a persistent gap between algorithmic adaptivity and pedagogical intent. While adaptive technologies hold promises for supporting learning at scale, their formative value depends on how learner data are interpreted and used to generate meaningful feedback and instructional response. This gap motivates the present work-in-progress study, which systematically examines how adaptive systems in STEM education are conceptualized, designed, and theoretically grounded, with particular attention to their alignment with formative assessment principles.

2.0 Methods

This study employs a scoping review methodology to examine how adaptive systems in STEM education enact formative assessment principles. The review follows the PRISMA-ScR framework to support transparency and systematic reporting while allowing flexibility for conceptual exploration appropriate to a work-in-progress study.

2.1 Data Sources and Search Strategy

An initial comprehensive search was conducted across five databases central to STEM and engineering education research: Engineering Village (Compendex and Inspec), Scopus, IEEE Xplore, ERIC, and Web of Science. Search strings combined terms related to adaptivity and formative assessment, including *adaptive learning*, *adaptive assessment*, *assessment for learning*, *formative feedback*, and *STEM or engineering education*. This broad strategy was intentionally designed to capture diverse conceptualizations of adaptivity across disciplines. The initial search yielded over 8,000 records, reflecting both the rapid expansion of adaptive systems research and its conceptual fragmentation across educational and technical domains.

2.2 Screening and Deliberate Study Selection

Following deduplication, title and abstract screening was conducted to exclude studies that were clearly outside the scope of the review, such as non-educational applications, purely summative testing systems, or adaptive platforms focused solely on content recommendation without assessment or feedback components. Full-text screening was subsequently conducted on a narrowed subset of studies to examine system design, adaptive mechanisms, and theoretical framing in greater detail.

For the purposes of this Work-in-Progress paper, five studies were deliberately selected from the full-text screened corpus using a theory-driven approach. Selection was guided by two criteria: (1) explicit articulation of adaptive formative assessment, defined here as systems that integrate adaptivity with formative feedback intended to support learning, reflection, or instructional response; and (2) sufficient detail across four analytic dimensions central to this study: adaptive mechanisms and feedback design, models and learner data, learning outcomes and formative alignment, and cross-cutting theoretical patterns. These dimensions structure the Results section and guided the focused synthesis presented in this WIP paper.

2.3 Data Extraction and Analysis

The selected studies were analyzed using a structured analytic framework aligned with the study's research questions. Data extraction focused on:
(1) adaptive design features and mechanisms;
(2) models and algorithms supporting adaptivity;
(3) explicit or implicit grounding in formative assessment theory; and
(4) types of learner data used to drive adaptation, including cognitive, affective, and behavioral indicators. An inductive–deductive coding approach was employed, drawing on formative assessment theory to guide initial codes while allowing additional themes to emerge across studies.

2.4 Work-in-Progress Positioning

Because this paper represents an early phase of a larger dissertation project, findings are illustrative rather than exhaustive. The deliberate focus on a small, theory-relevant subset of studies allows this WIP paper to surface conceptual patterns and gaps that will guide the subsequent full scoping review and the design of a Cognitive–Affective–Behavioral adaptive formative assessment prototype in engineering education.

3.0 Results

This section presents a focused synthesis of five deliberately selected studies that examine adaptive formative assessment systems in STEM and related domains. Although the initial search yielded over 8,000 records, this focused subset enables deeper conceptual analysis of system design and theoretical alignment. Findings are organized into four analytic dimensions: Adaptive Mechanisms and Feedback, Models and Learner Data, Learning Outcomes and Formative Alignment, and Cross-Cutting Patterns.

3.1 Adaptive Mechanisms and Feedback

Across the reviewed studies, adaptivity was primarily implemented through performance-based mechanisms, including dynamic item selection, sequencing, and repeated practice. Most systems relied on computerized adaptive testing (CAT) or mastery-based approaches to adjust task difficulty based on learner responses [11, 12]. Feedback design varied considerably. Some systems provided minimal correctness-based feedback, while others incorporated explanatory or interactive feedback intended to support conceptual understanding and self-monitoring [13].

3.2 Models and Learner Data

Psychometric and probabilistic models dominated system design, including IRT-based CAT and Bayesian updating. A small number of studies extended these models to support iterative formative cycles, accounting for forgetting or repeated practice rather than one-time evaluation [12]. Despite these advances, adaptivity remained largely cognitively focused, with limited incorporation of affective or behavioral data. Context-aware adaptations were present but uncommon [11].

3.3 Learning Outcomes and Formative Alignment

Most studies reported positive associations between adaptive system use and learning outcomes, such as improved quiz performance, increased engagement, or higher summative assessment scores. For example, repeated engagement with adaptive formative quizzes was associated with improved examination performance and sustained participation [14]. However, evidence of how feedback directly supported learning improvement was often indirect, inferred from performance gains rather than explicit learning processes.

3.4 Cross-Cutting Pattern

Overall, the synthesis reveals a persistent gap between algorithmic adaptivity and formative assessment principles. While systems demonstrate strong technical capabilities, explicit articulation of how adaptive feedback informs learner reflection or instructional action remains limited [15]. These findings underscore the need for clearer design frameworks that integrate adaptive mechanisms with formative interpretation and response. Across the reviewed studies, formative intent was often implicit rather than explicitly operationalized within system architecture, suggesting that pedagogical alignment remains subordinate to algorithmic precision.

4.0 Conclusion and Future Directions.

This work-in-progress study examined how adaptive systems in STEM and engineering education enact formative assessment principles through a focused synthesis of five theory-relevant studies. The findings indicate that while adaptive systems demonstrate strong technical capabilities, adaptivity is most often operationalized as performance optimization rather than as a formative process that supports feedback, reflection, and instructional response. Explicit grounding in formative assessment theory remains limited, and learner modeling is largely confined to cognitive performance, with minimal attention to affective or behavioral dimensions. These patterns reveal a persistent gap between algorithmic adaptivity and pedagogical intent. Ongoing work will extend this synthesis to a larger corpus and develop a conceptual taxonomy for Adaptive Formative Systems. This taxonomy will inform the design and pilot testing of a Cognitive–Affective–Behavioral adaptive formative assessment prototype aimed at supporting learning in engineering education.

5.0 References

[1] P. Black and D. Wiliam, "Assessment and classroom learning," *Assessment in Education: principles, policy & practice,* vol. 5, no. 1, pp. 7–74, 1998.

[2] D. J. Nicol and D. Macfarlane-Dick, "Formative assessment and self-regulated learning: A model and seven principles of good feedback practice," *Studies in higher education,* vol. 31, no. 2, pp. 199–218, 2006.

[3] J. W. Pellegrino, "Assessment of and for learning," in *International handbook of the learning sciences*: Routledge, 2018, pp. 410–421.

[4] R. M. Felder and R. Brent, *Teaching and learning STEM: A practical guide*. John Wiley C Sons, 2024.

[5] W. J. Van der Linden and C. A. Glas, *Elements of adaptive testing*. Springer, 2010.

[6] R. S. J. de Baker and P. S. Inventado, "Chapter X: educational data mining and learning analytics," *Comput. Sci,* vol. 7, pp. 1–16, 2014.

[7] J. Qadir *et al.*, "Leveraging the force of formative assessment C feedback for effective engineering education," 2020.

[8] P. Long and G. Siemens, "Penetrating the fog: Analytics in learning and education," *EDUCAUSE Review (Online),* 2011.

[9] R. Pekrun and L. Linnenbrink-Garcia, "Introduction to emotions in education," in *International handbook of emotions in education*: Routledge, 2014, pp. 1–10.

[10] S. D'Mello and A. Graesser, "Dynamics of affective states during complex learning," *Learning and Instruction,* vol. 22, no. 2, pp. 145–157, 2012.

[11] F. E. Louhab, A. Bahnasse, and M. Talea, "Towards an adaptive formative assessment in context-aware mobile learning," *Procedia Computer Science,* vol. 135, pp. 441–448, 2018.

[12] A. C. Yang, B. Flanagan, and H. Ogata, "Adaptive formative assessment system based on computerized adaptive testing and the learning memory cycle for personalized learning," *Computers and Education: Artificial Intelligence,* vol. 3, p. 100104, 2022.

[13] M. Marchisio, T. Margaria, and M. Sacchet, "Automatic formative assessment in computer science: Guidance to model-driven design," in *2020 IEEE 44th Annual Computers, Software, and Applications Conference (COMPSAC)*, 2020: IEEE, pp. 201–206.

[14] S. Gupta, N. Ojeh, B. Sa, M. A. A. Majumder, K. Singh, and O. P. Adams, "Use of an adaptive e-learning platform as a formative assessment tool in the cardiovascular system course component of an MBBS programme," *Advances in Medical Education and Practice,* pp. 989–996, 2020.

[15] S. K. Banihashem, D. Gašević, O. Noroozi, H. Jarodzka, D. Joosten-ten Brinke, and H. Drachsler, "Optimizing formative assessment with learning analytics," *Review of Educational Research,* p. 00346543251370753, 2025.