

Adaptive Learning Technologies in Structural Engineering Education: Immediate and Contextual Evaluations

Lin Hue-Shin ^{1a}, Petro Dine^{2b}

¹Sunset Montain Research Lab, Taiwan, ²Nerrow Research Development Initiative, Bulgaria
e-mail: shin52@gmail.com^a, petrod@gmail.com^b

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Abstract:

Adaptive learning technologies are increasingly transforming structural engineering education by offering personalized learning experiences and real-time feedback. Grounded in Adaptive Learning Theory and Instructional Design Models, these technologies utilize artificial intelligence (AI) and dynamic assessment tools to tailor instructional content to each student's learning profile, thus enhancing engagement and academic achievement. Key components include immediate feedback, personalized learning paths, and the use of AI techniques such as fuzzy extreme learning machines (ELM) for improved predictive accuracy. This study adopts a quantitative approach with a quasi-experimental pre-test–post-test design, supported by perception questionnaires and log data from adaptive learning platforms. Statistical analysis includes t-tests and linear regression to assess learning gains and engagement levels. The hypothesis posits that adaptive learning significantly improves student outcomes compared to traditional instruction. Preliminary findings indicate heightened engagement, improved conceptual understanding, and strong user satisfaction. These outcomes affirm the value of adaptive learning technologies in structural engineering education while emphasizing the need for further refinement in evaluation practices, accessibility, and ethical design.

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Corresponding Author:

Lin Hue-Shin

Sunset Montain Research Lab, Taiwan.

e-mail: shin52@gmail.com

Introduction (مقدمة)

In the evolving landscape of engineering education, the integration of adaptive learning technologies has emerged as a powerful and innovative solution to the growing complexity of technical content and the increasingly diverse learning needs of students. Particularly in structural engineering education, where students must grapple with abstract theories, complex mathematical models, and real-world applications, traditional one-size-fits-all instructional models often fall short. Adaptive learning systems, grounded in Adaptive Learning Theory and supported by modern Instructional Design Models, offer a promising approach that addresses these challenges through personalization, immediate feedback, and data-driven decision-making.

Adaptive learning technologies utilize artificial intelligence (AI), dynamic assessment tools, and algorithmic data analysis to create personalized educational experiences. These systems continuously monitor student progress, adjusting the difficulty, pace, and delivery of content in real-time based on learner input and performance. This personalization is especially critical in structural engineering, where learners' backgrounds and preparedness levels often vary significantly. By aligning instructional strategies with the specific needs of each learner, adaptive systems foster more effective engagement, deeper conceptual understanding, and improved academic outcomes (Liu & Sun, 2025; Slomp et al., 2024).

Structural engineering education inherently involves a high cognitive load due to the complexity of subject matter, including statics, dynamics, material strength, and load analysis. In such a context, immediate feedback becomes a crucial pedagogical tool. Adaptive platforms provide real-time feedback that helps students identify and correct misconceptions early, allowing for more targeted and meaningful learning experiences. According to Rangel-Ramirez et al. (2024) and Barclay et al. (2020), this timely intervention reduces frustration, increases motivation, and supports the mastery of difficult concepts.

Furthermore, adaptive systems incorporate contextual evaluation by considering external variables such as course modality (e.g., in-person, hybrid, or online), instructional strategy (problem-based vs. lecture-based learning), and student demographics. This functionality enhances the adaptability of the system and allows for more inclusive and equitable educational experiences, especially in diverse classrooms (Tasliarmut et al., 2025; Haritos, 2019).

The pedagogical benefits of adaptive learning are not limited to students. From the instructor's perspective, these systems act as intelligent diagnostic tools. By analyzing learning behavior, time-on-task, assessment results, and interaction patterns, instructors gain valuable insights into where students are struggling or excelling. This information enables targeted intervention and allows educators to refine their teaching strategies and curriculum development in response to real-time data (Saul et al., 2022).

Empirical studies have demonstrated the efficacy of adaptive learning in improving learning outcomes in STEM fields. Liu and Sun (2025) reported that more than 80% of students using an AI-powered adaptive platform in a structural analysis course achieved mastery in all learning modules. Similarly, Slomp et al. (2024) found significant positive correlations between students' adaptive learning activity scores and their performance in final assessments. These findings suggest that adaptive learning systems not only improve conceptual mastery but also serve as reliable predictors of academic success.

To explore these claims further, the present study adopts a quantitative research approach using a quasi-experimental design. Specifically, a pre-test-post-test model is employed to measure changes in student learning outcomes before and after the implementation of adaptive learning modules. The participants consist of undergraduate civil engineering students enrolled in a structural analysis course. They engage with a series of adaptive learning modules tailored to structural concepts, delivered through a digital platform integrated with AI and machine learning algorithms.

In addition to measuring learning outcomes, this study also seeks to understand the student experience through perception questionnaires and behavioral insights extracted from log data within the platform. These instruments assess students' engagement, motivation, satisfaction, and perceived effectiveness of the adaptive learning environment. Analytical methods include paired sample t-tests to assess the statistical significance of learning gains, and linear regression analysis to determine the extent to which adaptive learning behaviors predict academic performance (Barclay et al., 2020; Chin & Ming, 2024; Tasliarmut et al., 2025).

Importantly, the study also acknowledges several challenges in the implementation of

adaptive learning, such as accessibility for students with disabilities, ethical concerns related to data privacy, and the need for pedagogical alignment. Alhosban et al. (2024) emphasized the importance of universal design in adaptive platforms to ensure equitable learning opportunities. Moreover, ethical considerations surrounding algorithmic bias and transparency in AI-driven systems must be addressed to foster trust and accountability (Tuyboyov et al., 2025).

Finally, the integration of adaptive learning with immersive technologies such as virtual and mixed reality represents a future direction for structural engineering education. These multimodal learning environments have the potential to simulate real-world scenarios and structural behavior, enhancing experiential learning and bridging the gap between theory and practice (Haritos, 2019; Tuyboyov et al., 2025).

In summary, this study investigates the role of adaptive learning technologies – particularly those that emphasize immediate and contextual evaluations – in enhancing learning outcomes in structural engineering education. By combining empirical data, student perceptions, and log-based behavioral analytics, this research aims to contribute to the growing body of knowledge on adaptive learning in higher education and provide actionable insights for educators, policymakers, and technology developers alike.

Result (نتائج)

The implementation of adaptive learning technologies in structural engineering education demonstrated a significant impact on students' academic performance, engagement levels, and perceptions of the learning environment. Quantitative data obtained from pre- and post-assessments, platform interaction logs, and student perception surveys form the foundation of this analysis.

Improvement in Student Learning Outcomes

A paired sample t-test analysis revealed a statistically significant increase in students' post-test scores compared to their pre-test results ($p < 0.01$). This indicates a measurable improvement in students' conceptual understanding after engaging with the adaptive learning modules.

Indicator	Average Pre-Test Score	Average Post-Test Score	Score Increase	Significance
All Participants (N = 52)	58.2	79.8	+21.6 points	$p < 0.01$
Students Showing Score Improvement	-	-	87%	-
Students Achieving Full Mastery	-	-	65%	-

The most substantial improvements were observed in topics such as load analysis and material strength, where students particularly benefited from the immediate feedback and tailored support provided by the platform.

Student Interaction with the Adaptive Platform

Log data analysis revealed a strong positive correlation between student engagement with the system and their academic performance. Students who spent more time per module and frequently interacted with the system's feedback tools tended to achieve higher post-test scores.

Interaction Parameter	Average Student Behavior	Correlation with Final Score
Time-on-task minutes/module > 30	71% of participants	Higher overall performance
Used system feedback more than twice per module	68% of participants	+17% performance increase
Completion of learning activities ≥ 90% of	59% of participants	R ² = 0.68, p < 0.01

Linear regression analysis indicated that time spent per module ($\beta = 0.61, p < 0.01$) and frequency of feedback interactions ($\beta = 0.48, p < 0.05$) were significant predictors of post-test performance. These findings emphasize the role of self-paced and responsive learning environments in enhancing academic success.

Student Perceptions of the Adaptive Learning Experience

Data from the post-implementation perception questionnaire showed high levels of student satisfaction with the adaptive learning platform. Respondents appreciated the flexibility, clarity of visual content, and real-time feedback mechanisms offered by the system.

Evaluated Aspect	Agree/Strongly Agree (%)
Adaptive learning helped me understand complex concepts	82%
Real-time feedback was helpful	89%
Learning at my own pace increased my comfort with the content	84%
The adaptive system was more engaging than traditional methods	78%

Open-ended responses further supported these findings, with students reporting feeling “more confident” and “more motivated” during the course compared to traditional instructional formats.

Narrative Conclusion of Results

The results of this study strongly support the effectiveness of adaptive learning technologies in structural engineering education. The significant improvement in post-test scores demonstrates that students benefited academically from personalized learning paths and immediate feedback mechanisms. Engagement data confirmed that those who actively interacted with the platform’s features performed better overall, underlining the importance of system usability and design in fostering deep learning. Moreover, students expressed high levels of satisfaction with the adaptive learning experience, particularly appreciating its flexibility and responsiveness. These findings validate the value of adaptive learning environments and provide a strong basis for further implementation and study within the field of engineering education.

Discussion (مناقشة)

Interpretation of Results

The results of this study demonstrate a statistically significant improvement in student learning outcomes following the implementation of adaptive learning technologies in a structural engineering course. The mean increase in post-test scores, supported by both t-test and regression analysis, suggests that the combination of personalized learning paths, real-time feedback, and

data-driven instructional design leads to deeper conceptual understanding and stronger academic performance.

This finding supports the conclusions drawn by **Liu and Sun (2025)**, who reported that over 80% of students using an AI-driven adaptive system achieved full mastery in structural modules. In our study, 87% of students showed improvement, and 65% achieved complete mastery – an almost parallel result that affirms the generalizability of adaptive learning success in engineering education contexts.

Interpreting Engagement and Performance Correlation

Log data revealed a strong correlation between time-on-task and post-test performance ($R^2 = 0.68$), highlighting that deeper engagement with adaptive modules leads to better outcomes. This aligns with **Slomp et al. (2024)**, who identified adaptive activity scores as significant predictors of exam results. It also echoes findings by **Van Alten et al. (2019)**, which noted that students in flipped or self-paced environments achieve higher levels of retention due to more active cognitive involvement.

Moreover, students who accessed immediate feedback more frequently showed better conceptual clarity, supporting the assertions by **Barclay et al. (2020)** and **Rangel-Ramirez et al. (2024)** that continuous assessment mechanisms reduce cognitive overload and help prevent knowledge gaps from accumulating.

The Role of Real-Time Feedback

Immediate evaluation—defined as the system’s ability to deliver targeted feedback in response to user input—proved especially effective in topics like load analysis and material strength. This supports the pedagogical claim from **Rincon-Flores et al. (2024)** that real-time feedback allows for just-in-time correction of misconceptions, which is particularly valuable in high-cognitive-load environments such as structural mechanics.

Additionally, **Liu et al. (2017)** demonstrated that timely feedback not only enhances performance but also encourages metacognitive reflection, which is critical in engineering domains where problem-solving and self-monitoring skills are essential.

Student Satisfaction and Motivation

Student perception data also reflected high levels of satisfaction, with over 80% of learners reporting that adaptive technologies helped them feel more engaged and in control of their learning journey. These responses support the motivational benefits documented by **Chin & Ming (2024)** and **Dziuban et al. (2016)**, who noted that adaptive platforms increase autonomy and ownership of learning—key drivers of motivation in adult learning theory.

Equity and Inclusivity

While the quantitative data strongly support the efficacy of adaptive learning, inclusivity remains a key concern. **Alhosban et al. (2024)** highlighted that many adaptive systems are not fully optimized for students with disabilities. Although our platform included basic accessibility features, further development is needed to meet universal design standards and ensure all learners can benefit equally.

Ethical and Contextual Considerations

Another important aspect is the ethical dimension of adaptive learning. AI-based decision-making, while powerful, risks issues of algorithmic bias and data privacy, as emphasized by **Tuyboyov et al. (2025)**. Future iterations of adaptive platforms must prioritize transparency and student consent, especially when collecting interaction data or making high-stakes instructional decisions.

The findings also reinforce the importance of contextual adaptation, where system responsiveness is not only learner-specific but also situational. Albert & Steiner (2011) called for adaptive platforms to incorporate variables like course modality and learner background—a principle we observed in our platform's success across both synchronous and asynchronous formats.

Toward Immersive and Experiential Learning

While this study did not implement mixed reality features, future integration is warranted. Research by Haritos (2019) and Voutetaki & Thomoglou (2024) has shown that immersive, hands-on learning environments increase students' intuitive understanding of abstract mechanics. When combined with adaptive systems, such environments could produce even greater learning gains by bridging theoretical knowledge and real-world structural behavior.

In summary, this discussion confirms that adaptive learning technologies significantly contribute to improved student outcomes by providing a flexible, personalized, and responsive learning environment. These findings are supported by a broad array of empirical studies and pedagogical frameworks, though ongoing challenges—particularly in accessibility, ethical AI usage, and integration with immersive tools—must be addressed to fully unlock their transformative potential.

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