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AI as a Teaching and Learning Partner: Integrating Artificial Intelligence into Hands-On Learning of Flexural and Shear Behavior in Reinforced Concrete Beam

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Abstract

Artificial intelligence (AI) is rapidly transforming the way engineering education is designed, delivered, and experienced. In engineering education, AI has strong potential to become a powerful partner that empowers both instructors and students. For instructors, AI can support curriculum design, optimize class activities, and provide data-driven insights for continuous improvement. For students, AI offers personalized guidance, computational support, and opportunities for deeper conceptual understanding when appropriately guided by engineering principles.

This paper presents the design, implementation, and evaluation of an AI-supported, hands-on learning activity integrated into an undergraduate reinforced concrete design course. The activity aims to strengthen students' understanding of flexural and shear behavior through a laboratory-based reinforced concrete (RC) beam loading experiment, followed by AI-supported activities. The activity utilizes three-point bending beam tests, where students observe cracking progression, deflection behavior, and ultimate failure in beams with different reinforcement configurations, including under-reinforced, over-reinforced, and shear-failure types. Building upon the hands-on experiment, the AI-enhanced module enables instructors to refine and personalize the project setup based on students' backgrounds, prior performance, and feedback collected from surveys and exam results.

Students were encouraged to explore three complementary learning strategies: (1) using AI independently without theoretical verification, (2) relying solely on theoretical analysis, and (3) applying AI under the supervision of their theoretical knowledge. Students compared predicted cracking and ultimate loads from each approach with experimental results and synthesized their findings in a comprehensive final report. The project demonstrates to the students how AI can effectively explain experimental outcomes. This work also demonstrates the role of AI in both instructional improvement and student learning outcomes, while conveying an essential message: AI without theoretical understanding can be misleading. However, AI guided by professional engineering knowledge and a proper framework becomes a powerful and reliable learning partner within the engineering classroom.

1. Introduction

Reinforced concrete design is a course that provides fundamental knowledge as part of the civil engineering curriculum and is particularly critical for students who intend to pursue structural engineering as a future career path. Undergraduate reinforced concrete courses play a central role in preparing students to understand how structures carry load, deform, crack, and ultimately fail. Reinforced concrete design courses typically emphasize the analysis and design of structural members subjected to flexure and shear. Students that show mastery of the course material must integrate knowledge from mechanics of materials, concrete and steel material behavior, and design specifications using applied techniques. However, many students struggle to connect abstract theoretical formulations and code-based equations with real structural behavior observed in engineering practice. Concepts such as cracking load, ultimate load, crack patterns, and failure modes are often difficult to fully grasp through lectures and calculations alone. Hands-on experimental activities during laboratory-based courses, or experiments embedded within the course can significantly enhance student learning by bridging the gap between theory and physical behavior [1]-[5]. By directly observing reinforced concrete members under load, students are better able to contextualize analytical predictions and develop physical intuition regarding the structural response. Hands-on learning serves as a powerful complement to traditional analysis and design-based instruction.

Over the past few years, artificial intelligence (AI) has been rapidly and profoundly influencing nearly every aspect of modern society, including engineering education. The emergence of widely accessible AI tools presents both opportunities and challenges for the educational system, affecting faculty roles, instructional methods, and student learning behaviors [6]-[9]. For faculty, thoughtful integration of AI tools can improve instructional efficiency and enable more personalized, data-informed teaching strategies. For students, appropriate use of AI has the potential to enhance learning efficiency and conceptual understanding. However, non-critical or an exclusive reliance on AI-generated results poses significant risks, particularly in civil engineering field where safety, reliability, and professional responsibility are crucial. AI outputs that are not consistently grounded in engineering theory, do not properly reference technical codes and structural requirements for proper design control, and therefore may be misleading or incorrect, especially for complex behaviors such as failure in reinforced concrete design. Therefore, training students to effectively use AI tools should take place within a framework in which AI is continuously supervised by knowledge-based expertise, including theoretical understanding, design principles, and engineering judgment.

This paper presents a learning module designed to help undergraduate students use AI appropriately in a hands-on study of the flexural and shear behavior of reinforced concrete beams. In this study, AI primarily refers to widely used large language model tools, such as ChatGPT and Gemini, although students were not limited to these platforms and were allowed to use any AI tool of their choice. The instructional module is designed to encourage students to develop productive and responsible learning habits that combine AI tools with theoretical verification and experimental validation. By embedding AI within a hands-on reinforced concrete beam testing activity, the module promotes a theory-supervised AI approach that maximizes the benefits of AI while ensuring the reliability and credibility of engineering outcomes. The following sections present the project background, experimental design, AI integration strategy, and assessment used to evaluate the effectiveness of the project.

2. Project background

2.1 Course context

The project was implemented in a 3-credit, required upper level undergraduate course, Reinforced Concrete Design, which is part of the ABET accredited civil engineering curriculum at Marquette University. The course is typically taken by junior or senior level students and is intended to provide a fundamental understanding of the behavior and design of reinforced concrete structural members. Major topics covered in the course include the flexural behavior of rectangular beams, shear behavior, flexural design, shear design, the analysis of T-beams and doubly reinforced beams, and serviceability considerations. In addition to learning theoretical background and design procedures, students are expected to connect course concepts with actual structural response. For this reason, instruction in the course is delivered through a combination of lecture-based teaching and hands-on experimental activities, allowing students to relate analytical methods to observed reinforced concrete behavior.

2.2 Project overview

The project consisted of three stages. In the first stage, students were introduced through lecture to the main failure modes of reinforced concrete beams under vertical loading, with emphasis on the theoretical background needed to distinguish flexural and shear behavior. In the second stage, students participated in a hands-on laboratory activity in which three full-scale reinforced concrete beams were tested. This allowed students to directly observe crack development, deformation, and distinct failure mechanisms, while also collecting key experimental data such as cracking load, ultimate load, and failure mode. In the final stage, students completed a group-based report in which they analyzed the cracking load, ultimate load, and failure behavior of their assigned beam using three different approaches: theoretical analysis, unconstrained AI analysis, and theory-supervised AI analysis. They then compared these results with experimental observations and discussed how theoretical guidance improved the reliability and interpretability of AI-supported analysis.

2.3 Learning objectives

(a) **Observe and learn** the different failure modes of reinforced concrete (RC) beams and understand the mechanism of each failure mode.

(b) **Understand and explain** the differences between theoretical and experimental failure loads to better grasp the LRFD design philosophy.

(c) **Integrate AI** into the learning process to assist in data analysis, prediction, and interpretation to improve experimental outputs.

(d) **Critically evaluate** AI outputs by direct comparison to theoretical calculations and define the role of an engineering expert in the design process.

3. Experimental design

3.1 Beam specimens and test setup

The reinforced concrete beams used in this study had nominal dimensions of 8 in. × 11 in. × 96 in., as shown in Fig. 1. A concentrated load was applied at midspan, and the simply supported span length was 88 in. At the time of testing, the actual average concrete compressive strength was approximately 5.7 ksi. All longitudinal and transverse reinforcement consisted of Grade 60 steel.

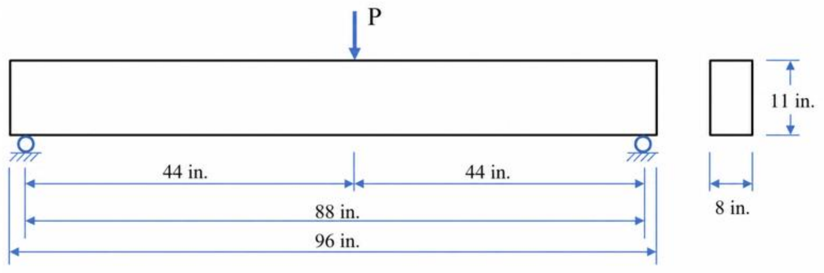


Fig. 1. Experimental setup and beam dimensions.

Three different reinforcement configurations were investigated, as shown in Fig. 2: an under-reinforced beam (Fig. 2a), an over-reinforced beam (Fig. 2b), and a shear-failure beam (Fig. 2c). One full-scale specimen was prepared and tested for each configuration.

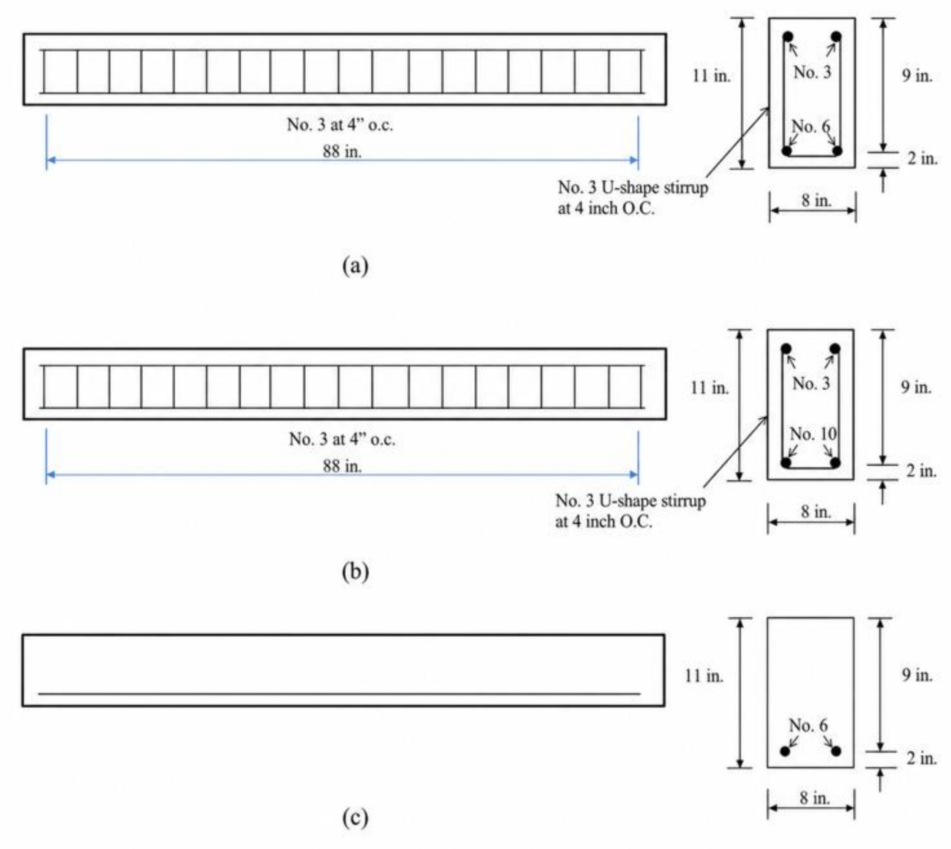


Fig. 2. Reinforcement configurations of the experimental beams: (a) under-reinforced beam, (b) over-reinforced beam, and (c) shear-failure beam.

All three beams were constructed using steel formwork. The longitudinal reinforcement and stirrups were placed within the formwork according to the designated reinforcement layouts, after which concrete was cast into the forms. The reinforcement details for each beam were predesigned to produce distinct failure modes. The reinforcement arrangements prior to concrete placement are shown in Fig. 3.

(a) (b) (c)

Fig. 3. The reinforcement arrangements formwork: (a) under-reinforced; (b) over-reinforced; and (c) shear failure beam.

3.2 Student tasks

Students were organized into small groups of four to five members, with each group assigned responsibility for one reinforced concrete beam specimen. During the laboratory testing, the group designated as the “beam owner” was positioned closest to the test setup and assumed primary responsibility for data collection and observation. Within each group, students divided tasks to ensure effective collaboration, including crack pattern, load tracking, and failure documentation. First, each group was required to measure the actual beam dimensions as well as the locations of the supports and applied load, rather than relying solely on nominal dimensions and designed locations. This requirement ensured that construction tolerances and specimen preparation variability were accounted for, leading to more accurate subsequent analyses and predictions. As loading applied, students were required to identify and mark all visible cracks on the beam and to monitor crack initiation and propagation throughout the test. Critical load values were recorded, including the cracking load corresponding to the first visible crack and the ultimate load at failure. Students also documented the complete failure process, including changes in cracking patterns, deformation behavior, and final failure mode. Fig. 4 shows the crack development measurement process and the three typical failure modes observed during beam testing.

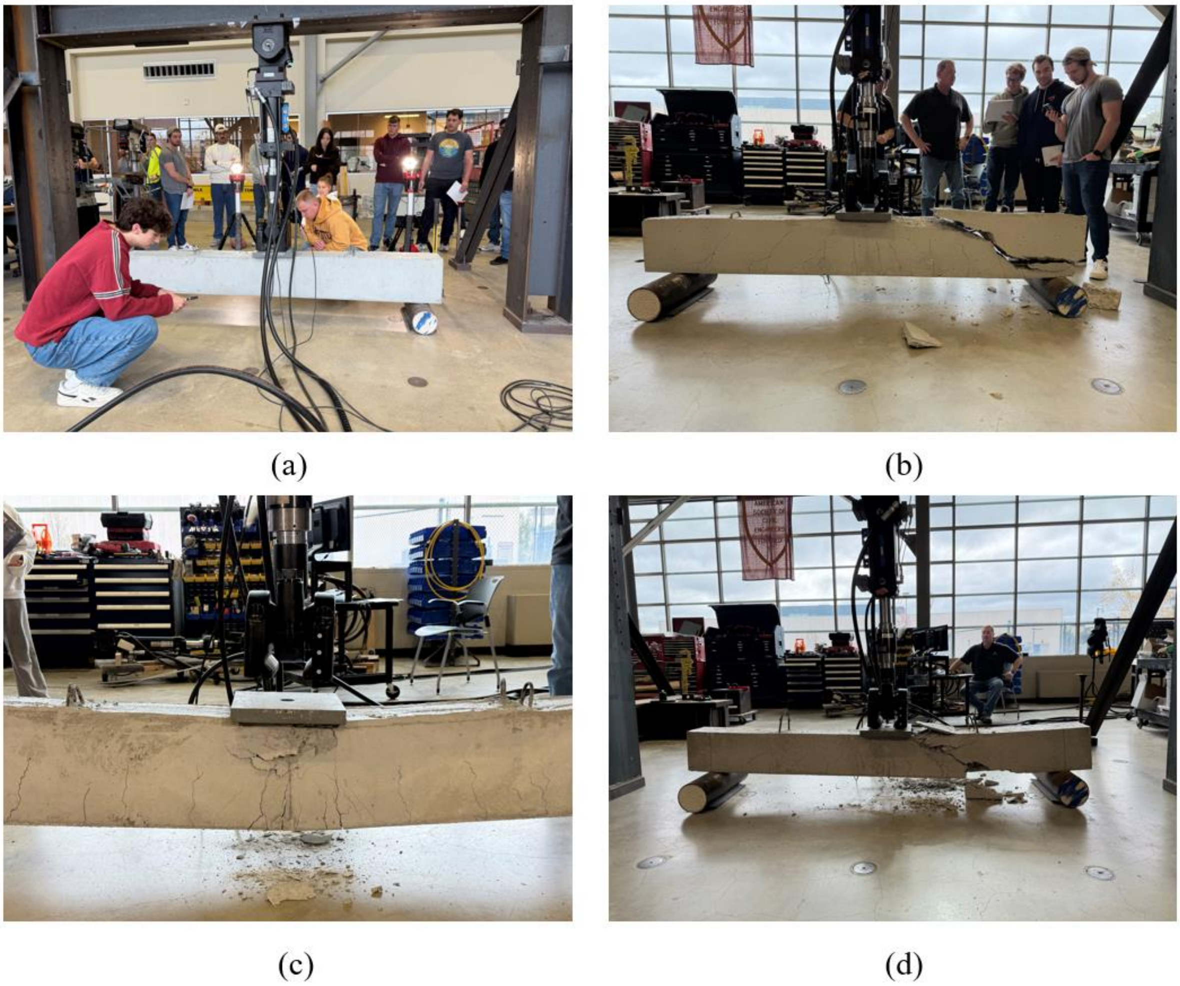


Fig 4. Experimental observation of crack development and failure modes in RC Beams: (a) Students measuring crack development, (b) Over-reinforced failure, (c) Under-reinforced failure, (d) Shear failure.

Although each group was assigned a specific beam, all students were present for and observed the testing of all three beam specimens. This allowed students to directly compare tension-controlled, compression-controlled, and shear-controlled failure behaviors and to develop a comprehensive understanding of how different reinforcement configurations influence reinforced concrete beam performance.

4. AI integration strategy

Artificial intelligence (AI) was intentionally integrated into the laboratory experiment from both instructional and student learning perspectives. Rather than positioning AI as a replacement for engineering analysis, the project framed AI as a supportive tool whose effectiveness depends on appropriate instructional design and supervision by theoretical knowledge. The main goal was to train engineering students to use AI effectively and ethically in the design of reinforced concrete.

4.1 AI integration from the faculty perspective

From the faculty perspective, AI offers significant opportunities to improve instructional efficiency. Hands-on learning activities have long been incorporated into design courses in the civil engineering classroom and have been demonstrated as an effective tool to help students connect theoretical knowledge with real structural behavior. With the rapid advancement of AI tools, instructors now have additional resources to refine these activities, improve the design prompt, and make the activity more effective and engaging to meet the students' needs.

In this project, faculty collaborated with AI tools during the instructional design phase to develop an impactful structured learning module that accounted for background of students and prior preparation. AI was used to assist in organizing the overall project workflow, refining the project's written requirements, and designing feedback rubrics that informed instructional sequence. Specifically, AI-supported development enabled the integration of a coordinated assessment framework, including a pre-lab survey /quiz and a corresponding post-lab survey / quiz, as summarized in Table 1. These instruments were used to assess student pre-lab preparation level, quantify learning progress, and characterize students' perceptions when given at check-points within the module. This allowed the instructors to adjust instructional emphasis and modify project expectations, according to student input.

Table 1. AI-assisted pre- and post-laboratory survey/quiz questions

Pre-Lab Assessment	Post-Laboratory Assessment
Reflections on AI Use	
1. How often do you use AI tools?	1. Since the pre-lab survey, how often did you use AI tools for this project?
2. When you use AI, what is the typical level of engagement?	2. What tasks did you use AI for?
3. Which AI tools or platforms have you used for engineering or study purposes?	3. How helpful was AI in improving your understanding of reinforced concrete behavior?
4. How confident are you in verifying whether an AI-generated engineering answer is correct?	4. When using AI for analysis, did you find any incorrect or misleading responses that required correction using theory?
5. Do you believe AI can replace theoretical understanding in engineering problem-solving?	5. Do you think AI becomes more effective when guided by theoretical understanding?
Background / Learning from the RC Beam Lab	
6. What are typical flexural or shear failure modes in RC beams?	6. How much did this lab improve your understanding of beam failure modes (under-reinforced, over-reinforced, shear)?
7. Match each failure mode to its general characteristic: a) Ductile behavior with large deflection b) Sudden and brittle failure	7. Match each failure mode to its general characteristic: a) Ductile behavior with large deflection b) Sudden and brittle failure

c) Crushing of concrete in compression before steel yields Under-reinforced: ___Over-reinforced: ____ Shear failure: ____	c) Crushing of concrete in compression before steel yields Under-reinforced: ___Over-reinforced: ____ Shear failure: ____
8. Briefly describe what happens to an RC beam as the load increases from zero to failure:	8. What was the most impressive aspect of observing the actual beam failure?
9. What factors might cause the experimental failure load to differ from the theoretical load?	9. Briefly describe what happens to an RC beam as the load increases from zero to failure:
10. What do you hope to learn from this lab and from applying AI tools during this activity?	
Self-Reflection / Suggestion	
11. On a scale of 1–5, how prepared do you feel for the RC beam test?	10. How would you rate your overall learning experience from this AI-supported hands-on lab?
12. What is your main concern or question before performing the beam test?	11. What are the two most important things you learned from this lab?
	12. How can this AI-supported RC beam lab be improved for future students?

4.2 AI integration from the student perspective

From the student perspective, the project provided a great opportunity to actively engage with AI tools while simultaneously developing critical awareness of the risks associated with reliance on AI generated results without critical input from the user. Students were explicitly encouraged to explore AI as a learning assistance tool while recognizing that engineering analysis requires understanding, validation, and professional judgment which all highly depend on theoretical knowledge.

The project was designed in three stages to support this learning progression. In the first stage, students established a solid theoretical foundation through lecture-based instruction on flexural and shear behavior of reinforced concrete beams. In the second stage, students observed full-scale reinforced concrete beam testing, allowing them to directly experience real structural behavior, cracking progression, and failure mechanisms. This hands-on experience provided essential physical context for the following analytical work. In the third stage, students conducted a comprehensive analytical study and submitted a group project report that required the use of three distinct approaches:

(a) **Unconstrained AI analysis:** Students used AI tools blindly, without their theoretical supervision of the input parameters or output responses with no iterative feedback in the process. The AI tool was expected to estimate the first-crack load, ultimate load, and likely failure mode based on rudimentary input prompting. Students were required to document the AI workflow / prompt, assumptions, and then provide the AI's output response in detail.

(b) **Theory-based analysis:** Students used theoretical methods learned in the reinforced concrete design course, along with actual measured beam dimensions and material properties, to individually calculate first-crack load and ultimate load for the experimental beams.

(c) **Theory supervised AI analysis:** Students reapplied AI tools under the supervision and verification of theoretical knowledge, comparing AI generated results with analytical calculations and experimental observations. Students summarized how this guided use of AI improved accuracy, reliability, and interpretability.

(d) **Comparison to experimental results:** Students compared each of these three analytical approaches (a-c) to measured values achieved through hands-on experimental data collected during the laboratory experiments.

Finally, students completed a reflective discussion by comparing all four sets of results: experimental results, theoretical predictions, unconstrained AI predictions, and theory-supervised AI predictions. Although all four were included in the comparison, the main focus was on examining the differences among theoretical, unconstrained AI, and theory-supervised AI results in relation to the experimental data. This reflection helped students identify the limitations of AI use without theoretical guidance, recognize the value of engineering knowledge in improving AI-supported analysis, and better understand how AI can be used more reliably in reinforced concrete design.

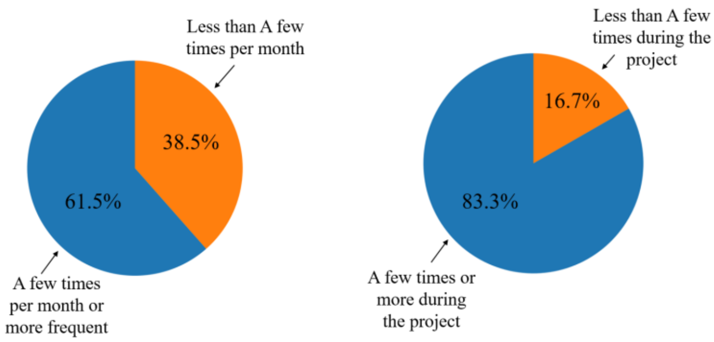
5. Assessment results and discussion

To evaluate the effectiveness of proposed project, evidence was collected from three sources: pre-lab survey, post-lab survey, and student group project report. These data provided insight into student participation and learning gains. A total of 14 students took part in the project, 13 completed the pre-lab survey, 12 completed the post-lab survey, and 3 group reports were reviewed as part of the final project submission.

5.1 pre- and post-lab survey results

In this study, the pre- and post-lab surveys were used to evaluate the frequency of students' use of AI tools, their perceptions of AI's contribution to learning, and their understanding of reinforced concrete beam failure mechanism. Overall, the results show that the proposed project helped improve both students' conceptual understanding and their awareness of how AI should be used in engineering learning.

Regarding the frequency of AI tools use, 61.5% of students (8 out of 13) in the pre-lab survey reported using AI tools a few times per month, indicating relatively light but already established prior use. In the post-lab survey, 83.3% of students (10 out of 12) reported using AI tools a few times or more during the project. This suggests that the project played a certain role in encouraging students to use AI more actively, even though they were already familiar with AI tools before the project. Fig. 5 compares the frequency of AI tool use before and during the project.

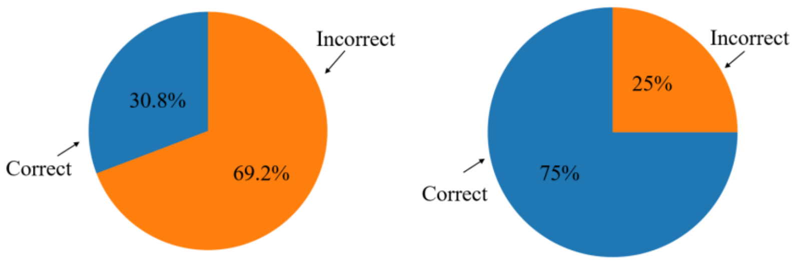


(a) before the project (b) during the project

Fig. 5. AI tool use frequency before and during the project

Students' perceptions of AI tool's contribution to learning were generally positive. In the post-lab survey, 16.7% of students reported that AI tools were extremely helpful, 41.7% found it helpful, 25.0% were neutral, and 16.7% said it slightly helpful. These responses indicate that most students viewed AI tools helpful for learning, while also suggesting that their educational value depended on how effectively it was used within the project.

The most notable improvement was observed in students' ability to identify reinforced concrete beam failure modes. In the pre-lab assessment, only 30.8% of students answered the failure-mode question correctly, whereas 69.2% answered incorrectly. More specifically, 76.9% of students were unable to clearly classify the three beam failure types prior to the lab activity. In the post-lab survey, however, 75.0% answered correctly and 25.0% answered incorrectly. This clear improvement suggests that the combination of lecture instruction, direct observation of beam behavior during testing, and AI-supported analysis substantially improved students' understanding of the three common failure modes of reinforced concrete beams: under-reinforced, over-reinforced, and shear failure. The comparison of students' understanding of RC beam failure mechanism before and after the project is shown in Fig. 6.



(a) before the project (b) after the project

Fig. 6. Comparison of students' understanding of RC beam failure mechanism before and after the project

5.2 Discussion of student group project results

The student group project provided a more direct evaluation of how students used experimental observations, theoretical knowledge, and AI tools to analyze reinforced concrete beam flexural behavior. The class was divided into three groups, and each group was assigned one beam with a different failure mode. During testing, each group recorded the failure process of its beam and the key values, including cracking load, ultimate load, and observed failure mode. After the test, each group analyzed its beam using three approaches: theoretical analysis, unconstrained AI analysis, and theory-supervised AI analysis. The summarized results from the three groups are presented in Table 2. There was a reasonable difference between the experimental results and the predicted values. These differences are expected because of uncertainties in specimen preparation, material variability, measurement, and observation during testing. However, the main focus of this study was not to eliminate all errors, but to examine whether theory-supervised AI could provide better predictions than unconstrained AI when compared with theoretical calculations and experimental results.

Table 2. Summary of experimental, theoretical, and AI-based results from group reports

		Experimental Loads (ksi)		Theoretical Prediction (ksi)		Unconstrained AI Prediction (ksi)		Supervised AI Prediction (ksi)	
Group	**Failure Mode**	P_{cr}	P_u	P_{cr}	P_u	P_{cr}	P_u	P_{cr}	P_u
1	Over-reinforced	1.6	30	4.17	36.51	3.2	26	3.2	36.5
2	Under-reinforced	5	30.52	5.59	26.62	9.21	51	7.09	24.62
3	Shear failure	6.9	19.47	5.38	16.97	4	15	4.8	17

Note: P_{cr} is cracking load, P_u is ultimate load.

For the over-reinforced beam group, the theory-supervised AI approach reduced the error in ultimate load prediction from 27.7% to 0.02% when compared with the theoretical prediction. The students found that the unconstrained AI result was less accurate because ChatGPT did not recalculate the updated depth of rectangular compression block and distance from the extreme compression fiber to the neutral axis values after recognizing that the beam was over-reinforced, and instead continued using the original values. Once this part was corrected and theoretically guided, AI became a much more accurate tool. For the under-reinforced beam group, the theory-supervised AI approach also gave much better results than unconstrained AI. The prediction error for cracking load was reduced from 65% to 27%, while the error for ultimate load was reduced from 91.6% to 7.5%. The students reported that this improvement came from providing AI with the necessary formulas for calculating both the first cracking load and the failure load, instead of allowing AI to choose its own method without constraints. For the shear failure beam group, the theory-supervised AI approach again showed clear improvement. The cracking load prediction error was reduced from 29.6% to 11.6%, and the ultimate load prediction error was reduced from 12.3% to 0.2%. Students found that the unconstrained AI analysis did not properly consider shear failure and instead treated the problem more like an under-reinforced or over-reinforced flexural case. Once shear failure related guidance was added, the supervised AI result became much more reasonable.

Overall, the group project gave students a clear understanding that unconstrained AI without theoretical guidance is not always reliable in engineering problems. At the same time, the results showed that when AI is supervised by theoretical knowledge, it can become a much more effective and accurate tool for engineering analysis. This comparison helped students better understand both the value and the limitations of application of AI tools in reinforced concrete design.

6. Limitation and future work

Future assessment and continuous improvement of this project will continue to combine traditional evaluation methods with AI-assisted analysis. AI tools can be used to synthesize and analyze multiple sources of student performance, including pre- and post-laboratory surveys/quizzes and group project reports. This can help improve the instructional workflow for faculty while also providing students with more timely, targeted, and personalized feedback. By examining trends in student responses and analytical outcomes, instructors can gain deeper insight into the real-time learning process of their students, work towards improving the conceptual development, and correct common misconceptions. In addition, AI-assisted analysis can support the development and refinement of standards-based grading rubrics that evaluate student performance more consistently and transparently across multiple learning areas, including theoretical analysis, effective integration of AI into engineering problem-solving, and critical reflection on results from different analysis approaches. In future offerings of the course, these AI-supported strategies can be used to guide instructional adjustments and continuous improvement, allowing instructors to refine course emphasis, project design, and assessment methods based on data-informed insights.

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