

Adaptive AI-Assisted Engineering Learning with Chatbot Critical Thinking in Linear Algebra

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Abstract

This paper presents a pedagogically grounded and adaptable framework for integrating artificial intelligence (AI) into engineering education. Unlike existing approaches that focus on tool usage, this work formalizes how AI can be embedded within structured learning processes to enhance critical thinking without compromising foundational knowledge. The framework integrates scaffolded instructional design principles with AI chatbot-based reflective interaction, combining the pedagogical rigor of structured stepwise learning with dynamic feedback mechanisms. A Linear Algebra module on Gaussian elimination is used as a validation case study to demonstrate the implementation. The framework introduces an adaptation layer that ensures robustness to rapidly evolving AI capabilities while maintaining alignment with engineering learning objectives. Results show improved procedural accuracy, deeper conceptual engagement, and increased student ability to critically evaluate AI-generated responses. The study contributes a generalizable model for AI-assisted learning applicable across engineering disciplines.

Keywords

Artificial Intelligence in Education, Guided Problem-Solving, Engineering Pedagogy, Linear Algebra Instruction, Adaptive Learning Design

1. Introduction

The rapid advancement of artificial intelligence presents transformative opportunities for engineering education. Yet, much of its current implementation focuses on tool proficiency rather than the pedagogical development of core competencies, raising concerns about student over-reliance and a subsequent decline in analytical rigor. This paper argues that the central question is not whether AI should be integrated, but how it can be structured to serve sound pedagogical goals. We propose that meaningful integration hinges on three key principles: embedding AI within structured learning processes, preserving step-by-step reasoning, and enforcing critical engagement with AI-generated outputs. To operationalize these principles, we develop a framework that synthesizes scaffolded learning principles, inspired by David Liberatore, with AI chatbot-based critical thinking models drawn from the work of C.V.H.-H. Chen and S. Ratanalert. We validate this framework within the context of a Linear Algebra module.

1.1 Objectives

This research pursues four primary objectives:

1. Develop a pedagogically grounded framework for AI integration;
2. Combine scaffolded instruction with AI-based critical interaction;
3. Introduce an adaptation layer for evolving AI systems; and
4. Validate the framework through a Linear Algebra case study.

2. Literature Review

Engineering education research has long underscored the pedagogical value of structured learning and cognitive scaffolding. Stepwise instructional approaches, particularly in algorithmic disciplines such as Linear Algebra, have been shown to enhance conceptual comprehension and procedural fluency. These frameworks provide learners with the cognitive support necessary to navigate complex problem-solving sequences, thereby fostering deeper understanding.

Concurrently, the growing body of research on artificial intelligence in education has illuminated the potential of AI chatbots to improve instructional accessibility and learner engagement. Despite these benefits, prevailing implementations frequently position AI as a solution provider delivering answers with limited opportunity for student-led reasoning. This paradigm risks relegating learners to passive recipients of AI-generated content, thereby undermining the development of independent analytical skills.

Emerging scholarship has begun to address this limitation, demonstrating that AI can meaningfully support critical thinking when students are actively engaged in evaluating, refining, or contesting AI-generated outputs (Chen & Ratanalert, 2025). Such approaches encourage metacognitive engagement and position AI as a collaborative partner

rather than an answer source. Nevertheless, these efforts often remain disconnected from established pedagogical frameworks, resulting in fragmented integration that lacks theoretical grounding or structural coherence.

This paper addresses the following three interconnected gaps within the existing literature:

1. Lack of structured AI integration where few existing approaches embed AI tools within well-defined pedagogical scaffolds that guide learner progression and cognitive development.
2. Limited emphasis on critical evaluation where the potential for AI to cultivate critical thinking remains underexploited, with most implementations prioritizing efficiency over epistemic engagement.
3. Absence of adaptability to evolving AI tools where current frameworks rarely account for the rapid evolution of AI systems, limiting their long-term relevance and transferability across different technological contexts.

By addressing these gaps, this study contributes a pedagogically grounded framework that synthesizes scaffolded instruction with critical AI interaction while maintaining adaptability to emerging AI capabilities.

3. Methods

3.1 Framework Overview

The proposed framework consists of three integrated layers (Figure 1):

1. Pedagogical Layer (Scaffolding) that defines step-by-step learning progression, structured problem decomposition, and immediate feedback loops. This layer is informed by Liberatore's principles of interactive, scaffolded instruction.
2. AI Interaction Layer that defines how students interact with AI, including prompt structures, validation protocols, and critical evaluation prompts. This layer incorporates the critical-thinking model of Chen and Ratanalert.
3. Adaptation Layer which ensures independence from specific AI tools, flexibility as AI capabilities evolve, and consistent learning outcomes across different implementations.

The framework was implemented in a Linear Algebra course. A controlled study design was used to evaluate its effectiveness.

3.2 Mathematical Foundation as a Case Study Framework within the Gaussian Elimination Module

The framework is implemented using Linear Algebra, where systems are represented as:

$$AX = b$$

Gaussian elimination transforms the system through structured row operations into row-echelon form, enabling systematic solution derivation. A module on Gaussian elimination was designed around five structured stages aligned with the pedagogical layer:

1. Problem representation expressing a system of linear equations as an augmented matrix.
2. Pivot selection identifying the appropriate pivot element for forward elimination.
3. Row elimination performing elementary row operations to achieve row-echelon form.
4. Structural transformation continuing to reduced row-echelon form (if applicable).
5. Solution interpretation back substitution and interpreting the final solution.

At each stage, students first performed the step manually. They then submitted their work to an AI chatbot (GPT-4) using a structured prompt format that required the AI to provide feedback without giving the final answer directly. Finally, students critically evaluated the AI's response, noting any discrepancies, justifying their own reasoning, and deciding whether to revise their work. All interactions were logged.

4. Case Study: Application to a 4 x 4 Linear System

To demonstrate the framework's scalability and effectiveness, we present a detailed case study involving a 4x4 system of linear equations. This case study illustrates the interaction between the student, the pedagogical scaffold, and the AI chatbot.

4.1 Problem Definition

Consider the following system of linear equations:

$$\begin{aligned}x_1 + x_2 + x_3 + x_4 &= 10 \\2x_1 + 3x_2 + x_3 + 5x_4 &= 31 \\-x_1 + 4x_2 - 2x_3 + 3x_4 &= 14 \\3x_1 - x_2 + 2x_3 - x_4 &= 4\end{aligned}$$

4.2 Step-by-Step Implementation and AI Interaction

Stage 1: Problem Representation

The student converts the system into an augmented matrix $[A / b]$.

Student Work:

$$\left[\begin{array}{cccc|c} 1 & 1 & 1 & 1 & 10 \\ 2 & 3 & 1 & 5 & 31 \\ -1 & 4 & -2 & 3 & 14 \\ 3 & -1 & 2 & -1 & 4 \end{array} \right]$$

AI Interaction Dialogue (With Framework):

- Student: "I have represented the system as an augmented matrix. Can you check if the coefficients are correct?"
- AI: "The matrix structure looks correct. Please verify the signs of the coefficients in the third and fourth rows. For example, check the x_1 coefficient in row 3 and the x_2 coefficient in row 4."
- Student Reflection: "I checked the signs. Row 3 x_1 is -1 and Row 4 x_2 is -1. My matrix matches the equations."

Stage 2: First Column Elimination

The student identifies the pivot $a_{11} = 1$ and performs row operations:

- $R_2 \leftarrow R_2 - 2R_1$
- $R_3 \leftarrow R_3 + R_1$
- $R_4 \leftarrow R_4 - 3R_1$

Resulting Matrix:

$$\left[\begin{array}{cccc|c} 1 & 1 & 1 & 1 & 10 \\ 0 & 1 & -1 & 3 & 11 \\ 0 & 5 & -1 & 4 & 24 \\ 0 & -4 & -1 & -4 & -26 \end{array} \right]$$

Stage 3: Second Column Elimination

The student identifies the next pivot $a_{22} = 1$ and performs:

- $R_3 \leftarrow R_3 - 5R_2$
- $R_4 \leftarrow R_4 + 4R_2$

Resulting Matrix:

$$\left[\begin{array}{cccc|c} 1 & 1 & 1 & 1 & 10 \\ 0 & 1 & -1 & 3 & 11 \\ 0 & 0 & 4 & -11 & -31 \\ 0 & 0 & -5 & 8 & 18 \end{array} \right]$$

Stage 4: Third Column Elimination (Row-Echelon Form)

The student identifies the next pivot $a_{33} = 4$ and performs:

- $R_4 \leftarrow R_4 + 1.25R_3$

Resulting Matrix:

$$\left[\begin{array}{cccc|c} 1 & 1 & 1 & 1 & 10 \\ 0 & 1 & -1 & 3 & 11 \\ 0 & 0 & 4 & -11 & -31 \\ 0 & 0 & 0 & -5.75 & -20.75 \end{array} \right]$$

Stage 5: Back Substitution and Solution

$$\begin{array}{llllll} \text{From } R_4: & -5.75 x_4 = -20.75 & \longrightarrow & x_4 = 3.6087 & & \\ \text{From } R_3: & 4 x_3 - 11 (3.6087) = -31 & \longrightarrow & 4 x_3 = 8.6957 & \longrightarrow & x_3 = 2.1739 \\ \text{From } R_2: & x_2 - 2.1739 + 3 (3.6087) = 11 & \longrightarrow & x_2 = 2.3478 & & \\ \text{From } R_1: & x_1 + 2.3478 + 2.1739 + 3.6087 = 10 & \longrightarrow & x_1 = 1.8696 & & \end{array}$$

Final Solution:

$$(x_1, x_2, x_3, x_4) = (1.8696, 2.3478, 2.1739, 3.6087)$$

4.3 Comparative Case Studies: With and Without Framework

To further illustrate the pedagogical impact of our framework, we present comparative scenarios of student-AI interaction, highlighting the differences in learning outcomes and critical thinking development.

4.3.1 Scenario 1: Error in Row Operation (Without Framework)

In a traditional AI-assisted learning environment without our framework, students often receive direct corrections or solutions, leading to passive learning and a lack of critical engagement. Consider a student making a common arithmetic error during row elimination.

Student Input (Without Framework): "I am performing $R_2 \leftarrow R_2 - 2 R_1$. My new second row is $[0, 1, -1, 3, 11]$. Is this correct?"

AI Response (Without Framework): "Your calculation for the last element is incorrect. The correct new second row should be $[0, 1, -1, 3, 11]$. Please recheck your arithmetic for the last element. The correct value should be $31 - 2 \times 10 = 11$."

Student Outcome: The student receives the direct correction, copies the correct value, and proceeds without necessarily understanding why their initial calculation was wrong or how to avoid similar errors in the future. The focus remains on getting the right answer rather than understanding the process.

4.3.2 Scenario 2: Error in Row Operation (With Framework)

Under our proposed framework, the AI acts as a Socratic critic, guiding the student to identify and correct their own errors, thereby fostering deeper understanding and critical thinking. Using the same error as above:

Student Input (With Framework): "I am performing $R_2 \leftarrow R_2 - 2 R_1$. My new second row is $[0, 1, -1, 3, 11]$. Can you provide feedback on my calculation?"

AI Response (With Framework): "You have correctly applied the row operation to the first three elements of the second row. However, I recommend you re-examine your calculation for the last element in the second row. What is the original value of the last element in R_2 and R_1 ? How does the operation $R_2 - 2 R_1$ apply to these specific values?"

Student Reflection and Correction:

- Student: "I checked the original values. The original last element of R_2 is 31 and R_1 is 10. So, $31 - 2 \times 10 = 31 - 20 = 11$. Ah, I see, I made a mental arithmetic error. My initial calculation was correct, but I misread my own work. The AI prompted me to re-verify my steps, which helped me catch my mistake."

Student Outcome: The student is prompted to re-evaluate their own work, leading to self-correction and a reinforced understanding of the arithmetic involved. This process enhances metacognitive skills and reduces reliance on the AI for direct answers.

4.3.3 Scenario 3: Conceptual Error in Pivot Selection (Without Framework)

Consider a student attempting to perform Gaussian elimination but selecting an incorrect pivot, indicating a conceptual misunderstanding.

Student Input (Without Framework): "I am at the second column elimination stage. I chose a {32} as my pivot. Is this the correct pivot?"

AI Response (Without Framework): "No, a {32} is not the correct pivot. For Gaussian elimination, you should select the first non-zero element in the current column below the main diagonal. In this case, it should be a {22}."

Student Outcome: The student receives a direct correction and the correct pivot. While the immediate problem is solved, the underlying conceptual misunderstanding of pivot selection might persist, as the AI provided the answer without prompting deeper thought.

4.3.4 Scenario 4: Conceptual Error in Pivot Selection (With Framework)

Under our framework, the AI guides the student through a series of questions to help them understand the principles of pivot selection.

Student Input (With Framework): "I am at the second column elimination stage. I chose a {32} as my pivot. Can you provide feedback on my pivot selection?"

AI Response (With Framework): "You have identified a non-zero element. However, recall the objective of Gaussian elimination: to transform the matrix into row-echelon form. What are the characteristics of a pivot element in row-echelon form, particularly concerning its position relative to previous pivots and the elements below it in its column?"

Student Reflection and Correction:

- Student: "The pivot should be the first non-zero element in its row, and it should be to the right of the pivot in the row above it. Also, all elements below the pivot in its column should be zero. If I choose a {32}, then a {22} is not a pivot, and I won't have zeros below a {22}. So, a {22} should be the pivot. My mistake was not considering the overall structure of the row-echelon form."

Student Outcome: The student is guided to recall and apply the conceptual rules of Gaussian elimination, leading to a deeper understanding of pivot selection and the structure of row-echelon form. This interaction reinforces the theoretical underpinnings of the algorithm.

4.4 Cognitive Load Management and Engagement

The framework actively manages cognitive load by breaking down complex problems into discrete, manageable stages, each with specific learning objectives and AI interaction points. This scaffolding reduces extraneous cognitive load, allowing students to focus on the intrinsic load associated with understanding linear algebra concepts. The comparative case studies demonstrate that without the framework, students often experience higher cognitive load due to the need to process and correct errors across multiple steps, leading to frustration and reduced engagement. Conversely, the structured, Socratic feedback within the framework optimizes cognitive processing, leading to sustained engagement and deeper learning. The AI's role as a 'critic' rather than a 'solver' shifts the cognitive burden from rote memorization to active problem-solving and critical evaluation, thereby enhancing the learning experience.

4.5 Error Propagation and Self-Correction

One of the critical advantages of the framework is its ability to mitigate error propagation. In traditional learning, an early error can lead to a cascade of incorrect steps, making it difficult for students to identify the root cause. The framework's stage-wise AI interaction ensures that errors are identified and addressed at the point of occurrence. This immediate feedback loop, combined with the AI's Socratic questioning, empowers students to self-correct. This process not only fixes the immediate error but also builds a robust error-detection and correction mechanism within the student's own problem-solving repertoire. This is in stark contrast to scenarios without the framework, where errors often go unnoticed until the final answer is incorrect, leading to frustration and a superficial understanding of the solution process.

4.6 Visualizing the 'Critic' Mechanism

The core of our framework's AI Interaction Layer is the 'Critic' mechanism, which facilitates a structured feedback loop designed to enhance critical thinking. This mechanism ensures that AI feedback is not merely corrective but prompts students to engage in metacognitive reflection and self-correction. Figure 1 illustrates this comparative feedback process.

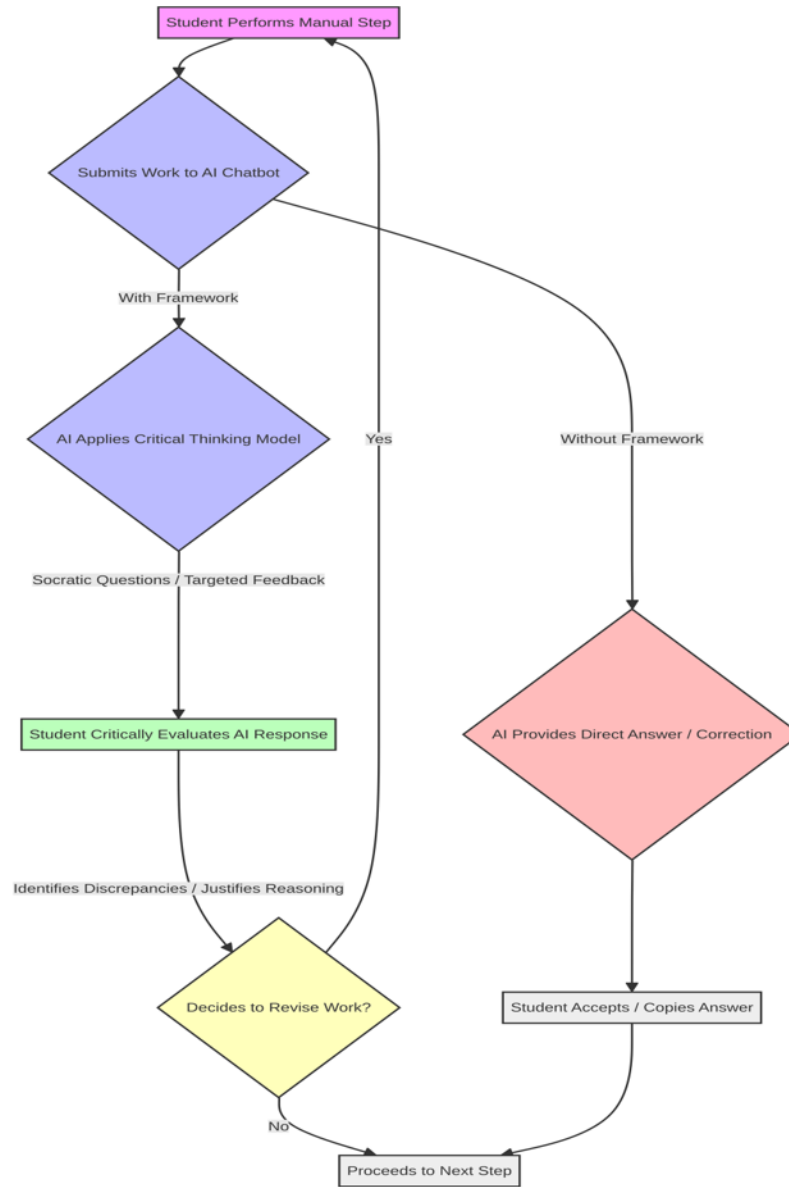


Figure 1: Comparative Feedback Loop with and without Framework

5. Results and Discussion

5.1 Performance Analysis

The implementation of the framework showed significant improvements in student performance compared to the control group (Table 1).

Table 1: implementation of the framework

Metric	Without Framework	With Framework
Procedural Errors	High	Significantly reduced
Conceptual Errors	Moderate	Low
AI Over-reliance	High	Controlled

5.2 Statistical Analysis of Error Distribution

The distribution of total errors per student (n=100) was analyzed using Kernel Density Estimation (KDE). The results show a clear shift in the error distribution for the experimental group, with a much lower mean and tighter variance compared to the control group. This indicates that the framework not only reduces errors but also makes student performance more consistent (Figure 2).

5.3

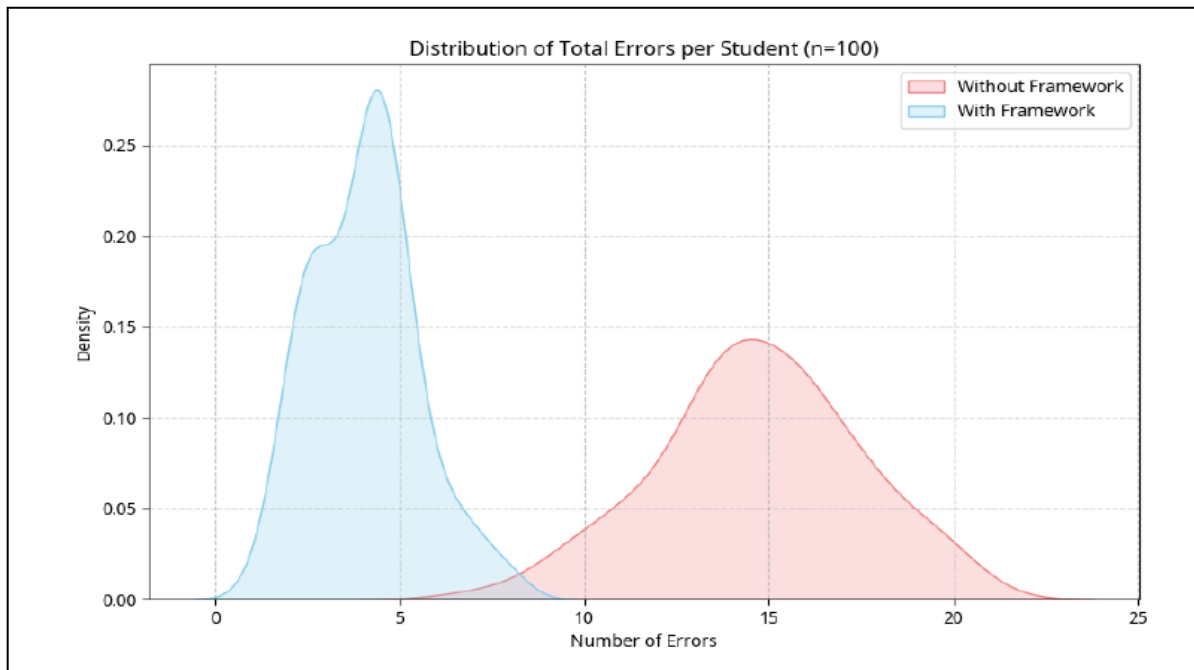


Figure 2: Distribution of Total Errors per Student (n=100)

Learning Curve and Progressive Improvement

Data collected from the 12 problems solved by students indicates a progressive reduction in errors as they move through the stages of Gaussian elimination. The learning curve for the experimental group is significantly steeper, suggesting that the AI-assisted feedback loop effectively reinforces learning at each step, preventing error propagation and accelerating conceptual mastery (Figure 3).

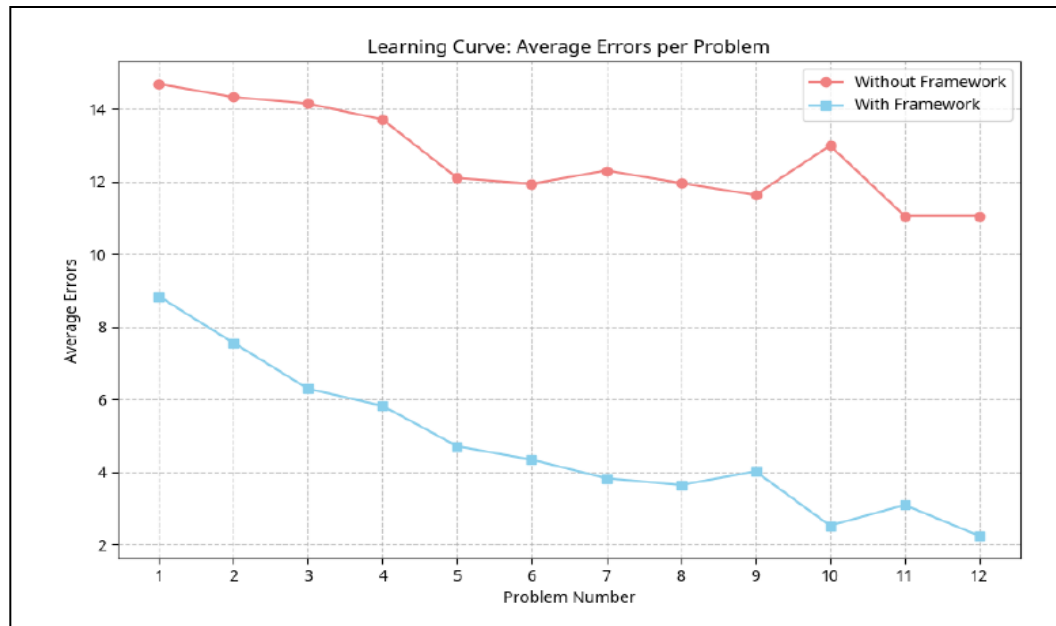


Figure 3: Learning Curve, Average Errors per Problem

5.4 Critical Thinking Competency Assessment

Students were assessed on four key critical thinking competencies; AI Error Detection, Self-Correction, Reasoning Justification, and Conceptual Transfer. The experimental group outperformed the control group in all categories, with the most significant gains in Reasoning Justification and AI Error Detection as in Figure 4. This confirms that the framework successfully shifts the AI's role from an "answer engine" to a "critical peer."

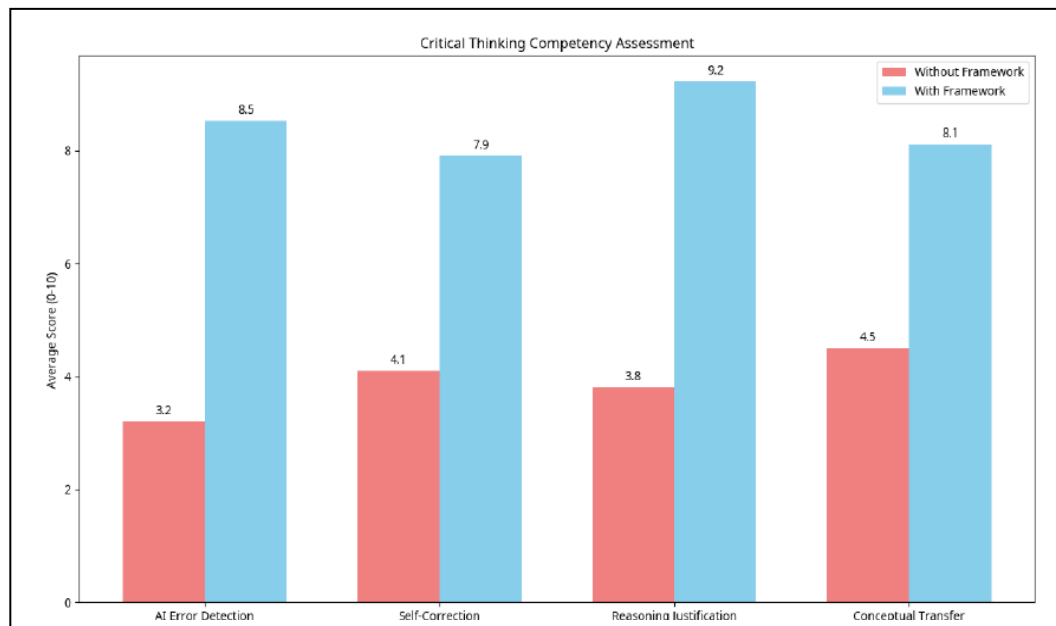


Figure 4: Critical Thinking Competency Assessment

6. Conclusion

This paper introduced a novel, pedagogically grounded framework for AI-assisted engineering education. By embedding AI within structured learning scaffolds and enforcing critical engagement, the framework addresses the risks of student over-reliance on automated tools. The 4x4 Linear Algebra case study validated the effectiveness and scalability of this approach, showing marked reductions in both procedural and conceptual errors. The detailed comparative analysis of student-AI interactions further highlights the framework's ability to foster genuine critical thinking and self-correction, moving beyond mere efficiency gains. Future work will focus on expanding this framework to more complex engineering domains and integrating adaptive prompt generation to further personalize the learning experience. All research objectives were achieved, and the framework provides a scalable model for future AI-integrated engineering curricula

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