From Simulation Prototyping to AI-Facilitated Argumentation: A Design-Based Approach to Fostering Design thinking in Engineering Education

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Abstract

Engineering technology education faces the ongoing challenge of equipping students with skills to master complex concepts through authentic design experiences. A key opportunity lies in integrating artificial intelligence with simulation tools to foster design thinking and economic decision making and science based knowledge. This paper explores the implementation of large language models alongside simulation software to enhance learning by design in project based settings.

Despite interest in emerging technologies, insufficient attention has been given to the synergy between these models and simulation based design. This study addresses the gap by grounding the approach in complex learning principles within a first year energy efficiency course. The intervention unfolded over two phases including an initial lecture based session introducing energy principles followed by assessments of conceptual understanding and self efficacy and metacognitive reasoning. This foundational knowledge prepared students for the subsequent design phase.

In the second phase, students used Aladdin simulation software to model a house with solar panels. Guided by design based learning, students clarified specifications such as budget constraints and net energy goals and environmental responsibilities. They then used the simulation tool to generate alternatives and prototype solutions and test performance. To augment this process, a conversational agent facilitated reflection and communication. Two variants were deployed including a scaffolded version providing structured prompts for scientific rationale and a non scaffolded version enabling open ended dialogue.

Data from assessments and reflections demonstrated significant gains in conceptual grasp and decision making confidence and the ability to articulate multifaceted design rationales. The integration of simulation for prototyping and artificial intelligence for reflective argumentation proved effective in deepening systems thinking and uncovering sustainability trade offs. This work illustrates the feasibility of combining these tools in design based learning and offers a scalable model for engineering technology education. By embedding reflection into simulation workflows, the approach enhances technical proficiency and promotes critical engagement with economic and social and environmental contexts.

Introduction

Engineering technology education emphasizes the integration of scientific principles, economic considerations, and design decision-making within authentic, practice-oriented contexts[1]. Yet, first-year students often struggle to meaningfully synthesize these elements when confronted with complex design problems[2]. Prior research highlights that embedding learning activities in authentic contexts is foundational to engineering technology education, as it supports students' ability to transfer theoretical knowledge to practical situations[3,4]. In particular, engagement with real-world design challenges has been shown to foster problem-solving, design thinking, and justification skills essential to engineering practice[5].

Energy simulation tools provide a particularly powerful authentic context by enabling students to explore realistic system behavior, constraints, and trade-offs while grounding design decisions in quantitative evidence. When coupled with advances in large language models (LLMs), these tools create new opportunities to scaffold student reasoning, reflection, and argumentation throughout the design process[6,7]. Rather than replacing student thinking, AI can function as a cognitive scaffold—supporting sense-making, prompting justification, and helping learners articulate and evaluate competing design alternatives.

This short paper presents a responsible implementation of an AI-supported energy design challenge in a first-year engineering course. The activity integrates energy simulation software with a custom LLM to support design thinking, evidence-based argumentation, and trade-off analysis within an authentic learning environment. The purpose of this paper is to inform and share a concrete instructional approach that demonstrates how AI can be used responsibly to support learning, while simultaneously teaching students how to critically and productively engage with AI as part of their engineering practice. By embedding AI within a holistic, design-based learning experience, this work contributes an example of how AI can complement—not replace—core engineering reasoning skills.

Methods

Participants and Context

The activity was implemented in Gateway to Engineering, a required first-year engineering course at a large Midwestern university. A total of 365 students participated across Spring 2025 (82 students across five lab sections) and Fall 2025 (283 students across nine lab sections), with 323 students completing all components of the activity. Figure 1 summarizes the student demographics by semester, including gender and race distributions. Overall, the cohort was predominantly male (80%), with 18% identifying as female. The racial composition was primarily White, followed by Asian and Hispanic students.

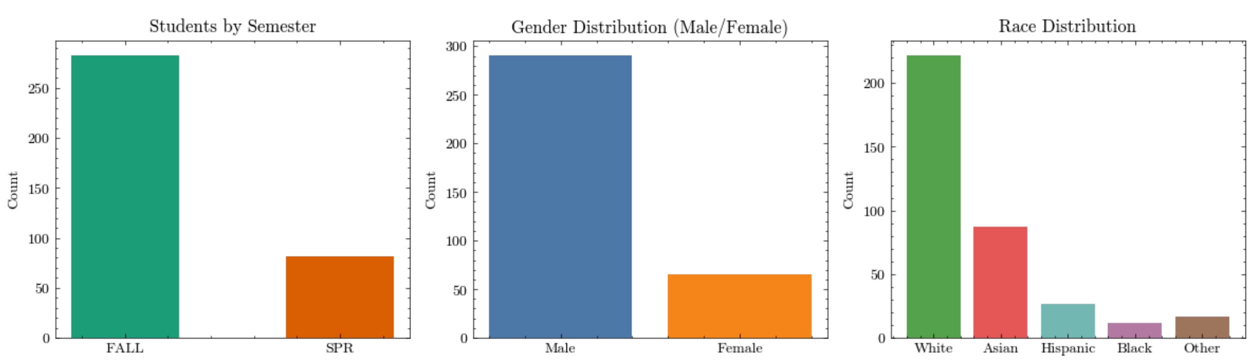

Figure 1: Demographic and semester distribution

Figure 2 presents the distribution of students' intended majors, showing the top seven categories. Mechanical Engineering Technology was the most common major, followed by students grouped as "Other" due to belonging to a minority degree in the course. Computer Engineering Technology constituted the next largest group, with smaller but comparable representations from Electrical Engineering Technology and Mechatronics Engineering Technology. A smaller number of students were enrolled in the Manufacturing Engineering Technology (MET) and Exploratory tracks. Overall, the distribution reflects a strong concentration in technology-focused engineering majors, with a long tail of less-represented programs.

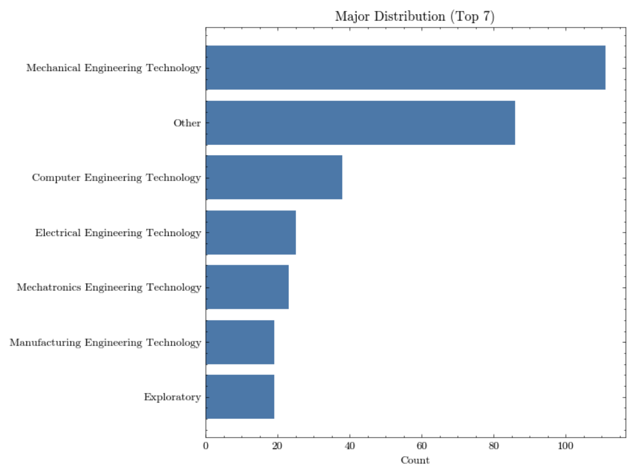

Figure 2: Major Distribution

Design Challenge and Procedure

Students engaged with a realistic case in which trees on one property cast shade on a neighbor's solar panels, lowering their energy output. With the Aladdin simulation tool—an energy modeling and experimental platform for rethinking engineering design in the age of AI, created by the Institute for Future Intelligence[8]—students repeatedly refined panel placement, tree trimming strategies, and house orientation while staying within financial and environmental limits, recording their choices in design journals.

The activity followed design-based learning stages: clarifying specifications, generating alternatives, prototyping, testing, and iterating. In the culminating phase, students defended their designs in a persuasive dialogue with one of two custom ChatGPT models (assigned by lab section): (1) **Scaffolded LLM**: Provided structured prompts requiring scientific principles, simulation evidence, and trade-off justification; (2) **Non-Scaffolded LLM**: Simulated an emotional, non-technical neighbor with superficial or irrational objections.

Assessment

Pre- and post-tests were administered as part of a convergent mixed-methods design to capture both learning outcomes and students' self-reported perceptions of their design reasoning. Quantitative measures included a five-item multiple-choice assessment of conceptual knowledge related to solar energy systems, as well as Likert-scale survey items adapted from the Intrinsic

Motivation Inventory. All Likert-scale items were rated on a 5-point scale (1 = Strongly disagree to 5 = Strongly agree).

Perceived design self-efficacy was assessed using three items examining students' confidence in designing solutions to real-world engineering problems, communicating and justifying design decisions, and completing engineering design tasks independently. Decision-making and trade-offs were measured through three items targeting students' perceived ability to evaluate cost–performance–sustainability trade-offs, make informed decisions under uncertainty, and consider multiple perspectives when selecting design solutions. Perceived metacognitive awareness and argumentative reasoning were assessed using three items that focused on students' reflection on their reasoning processes, identification of weaknesses or gaps in their own designs, and use of evidence (e.g., data, simulations, references) to support design claims.

Quantitative analyses focused on changes from pre- to post-test. Descriptive statistics were computed for all measures, and paired-samples t-tests were used to examine statistically significant changes in conceptual knowledge and self-reported constructs, with the significance threshold set at $\alpha = .05$. Given the exploratory nature of the study and the use of brief, classroom-appropriate scales, analyses were interpreted as inferentially cautious rather than confirmatory.

Qualitative data were collected through an open-ended post-survey reflection asking students how their interaction with the AI influenced their approach to the engineering design problem. These reflections provided insight into how students perceived the role of the AI in shaping their reasoning, justification strategies, and engagement with trade-offs, and were used to contextualize and triangulate the quantitative findings.

Results

Students demonstrated statistically significant gains across all measured outcomes (Table 1). Conceptual knowledge scores increased from pre-test ($M = 2.90$, $SE = 1.03$) to post-test ($M = 3.30$, $SE = 1.02$), indicating a significant improvement, $t(365) = 4.87$, $p < .001$, with a medium effect size ($d = 0.30$). Significant pre–post gains were also observed across all three self-reported constructs. Design self-efficacy increased with a medium effect ($d = 0.43$), reflecting greater confidence in solving real-world engineering problems, communicating and justifying design decisions, and completing design tasks independently. Decision-making related to cost–performance–sustainability trade-offs exhibited the largest improvement ($d = 0.40$), suggesting enhanced confidence in evaluating alternatives and managing uncertainty. Perceived metacognitive awareness and argumentative reasoning also increased significantly ($d = 0.28$), indicating greater self-reported reflection on reasoning processes, identification of limitations in design solutions, and use of evidence to support design claims.

In addition to these quantitative gains, students' perceptions of AI use in laboratory settings shifted positively following the activity, with an approximately 15% increase in positive sentiment. Qualitative reflections provided convergent evidence supporting the survey results, with many students describing deeper reasoning, clearer articulation of design justifications, and more deliberate use of evidence during the AI-mediated dialogue. Students frequently emphasized the need to anticipate counterarguments and explicitly justify trade-offs, particularly

Table 1: Summary of pre–post quantitative results across knowledge and self-reported constructs

Measure	**Pre-test** M	**Post-test** M	**SD / SE**	$t(df)$	d
Conceptual Knowledge	2.90	3.30	SE $\approx$ 1.03 / 1.02	$4.87(365)$	0.30
Design Self-Efficacy	3.83	4.10	SD $\approx$ 0.66 / 0.68	$3.52(322)$	0.43
Decision-Making & Trade-offs	3.49	3.80	SD $\approx$ 0.58 / 0.33	$7.33(322)$	0.40
Metacognition / Argumentation	4.01	4.20	SD $\approx$ 0.52 / 0.54	$3.41(322)$	0.28

when interacting with the scaffolded LLM. One representative student noted: "*While working to convince ChatGPT to install solar panels, I had to provide solutions and counter reasons...This made me think deeper about my reasoning and how I presented my research to others.*"

Discussion

The integration of simulation-based prototyping with AI-facilitated argumentation proved effective in fostering design thinking. Students gained conceptual knowledge, confidence in handling trade-offs, and metacognitive skills in justifying decisions — outcomes aligned with complex learning principles.

The scaffolded LLM prompted deeper reflection and evidence-based reasoning, while the activity's realistic context helped students uncover overlooked sustainability and economic factors. This approach is scalable, requiring only accessible simulation tools and LLM platforms.

Future work will examine differential effects of prompting styles on argumentation quality and explore adaptations for diverse learners.

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