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Promoting Design Thinking, Energy Science Learning, and Economic Decision-Making Through AI-Supported Simulation-Based Design

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Abstract

Engineering technology education often struggles to help students connect abstract energy concepts to authentic design contexts. This study examines the integration of an AI-supported scaffold within a first-year energy-efficiency design challenge. Students used a simulation tool to optimize a solar-powered house affected by tree shading, balancing technical, economic, and environmental constraints. A large language model served as a conversational design counterpart under two conditions: a scaffolded model that prompted evidence-based argumentation and a non-technical model that engaged in open-ended dialogue.

Pre- and post-test results indicated significant gains in conceptual knowledge and self-reported decision-making confidence. Student reflections suggested that AI-supported dialogue encouraged clearer justification of design choices and deeper consideration of trade-offs. Rather than isolating specific causal mechanisms, this study characterizes the overall impact of embedding AI-driven scaffolding within simulation-based learning. Findings suggest that structured AI interaction can support reflective reasoning and evidence-based design thinking in early engineering technology education.

Introduction

Engineering education, particularly in engineering technology, has long grappled with the inherent complexity of concepts and the critical need for students to connect theory with practical application [1]. Emerging technologies offer promising opportunities to overcome limitations of traditional classroom instruction and enhance students' technical skills and knowledge [2], [3]. Andre et al. conducted a comprehensive assessment that identified significant trends in the adoption of educational technologies, highlighting how successive waves of integration have rapidly transformed classrooms in response to evolving industry needs and technological progress [4]. Building on these historical patterns and with the boom of artifical intelligence (AI), the release of ChatGPT in November 2022 and subsequent developments in large language models (LLMs) represent a new wave with unique potential to foster creative learning, innovation, and deeper engagement in engineering contexts [5], [6].

This paper is motivated by the need to help students more effectively understand and engage with multifaceted topics in engineering technology. Specifically, it examines the integration of AI tools in a first-year design challenge that bridges science-based reasoning, economic decision-making, and engineering design — an interdisciplinary area where empirical research remains scarce [7].

The rise of LLMs as reflection partners, when thoughtfully combined with simulation tools, opens new pedagogical pathways to address these challenges and can impact student motivation and development [8]. In an era of rapid digital transformation, equipping students with competencies to navigate and lead in AI-augmented environments is increasingly essential. This work contributes to the body of knowledge by documenting a practical classroom implementation of AI scaffolding within a first-year engineering design challenge and by sharing key lessons learned from combining it with simulation-based learning.

The integration of AI into higher education has become a defining trend, with the potential to fundamentally reshape teaching, learning, assessment, and administrative processes [6], [9], [10]. Numerous studies have explored both the opportunities and challenges of AI applications in academic settings, identifying contexts where these tools prove particularly effective [5], [11]. For instance, Vidalis and Subramanian [10] reviewed how AI can strategically support teaching, learning, and assessment, while AI-driven analytics can enhance academic outcomes and institutional efficiency. Other researches have shown that AI enables real-time feedback for students and instructors, thereby enriching the overall learning experience [12], [13].

Recent efforts have begun incorporating AI into engineering education to improve instructional methods and student outcomes [10], [12]. Although the literature frequently highlights the promise of these tools, documented implementations in authentic classroom settings remain relatively rare. Due to their flexibility, LLMs have been adapted for varied roles, including coding tutors, brainstorming aids, and writing support [11]. Coding assistance has proven especially relevant in engineering, where tools like ChatGPT help students generate code, debug errors, and grasp complex algorithms [14]. These systems offer immediate, adaptive feedback that enables more effective engagement with programming concepts. Khanolkar et al. (2025) underscore the growing prevalence of such applications while emphasizing the need for more systematic, classroom-embedded studies [15]. Overall, while early explorations are encouraging, most remain preliminary and seldom report detailed results from real learning environments [11].

Prior work on AI in classrooms has largely concentrated on discrete, task-specific support, such as programming or writing assistance, but has paid less attention to the complex, integrative learning processes required for engineering. These processes demand that students transfer knowledge from lectures to novel, authentic scenarios, synthesizing technical reasoning with economic trade-offs and design judgment [16]. Despite growing interest in AI, a significant gap remains: the potential for AI to scaffold argumentation, guiding students to formulate evidence-based claims within integrated design experiences, remains minimally examined in engineering technology settings. Consequently, there is a need for classroom-based studies that move beyond AI's theoretical promise to explore its practical effectiveness in real-world educational practice.

This paper addresses these gaps through a classroom-based intervention in a first-year engineering design course. Following principles of complex learning design [16], we integrated a custom ChatGPT model as an interactive scaffold alongside a simulation tool to support students as they tackled an authentic energy-efficiency challenge. This AI counterpart was designed to prompt students to articulate arguments and justify design decisions in real time. By describing the implementation and reflecting on student outcomes, this work provides empirical insights into how AI-driven argumentation and structured reflection can be integrated into engineering technology curricula. The findings characterize how such a hybrid learning environment, combining simulation and AI supports student engagement with multifaceted design rationales and complex technical concepts.

Methods

Participants and Context

This study was conducted in a first-year engineering course, *Gateway to Engineering Technology*, during the energy unit at a large Midwestern university. A total of 365 first-year engineering students participated across two academic terms: Spring 2025 (82 students in five lab sections) and Fall 2025 (283 students in nine lab sections). Of these, 323 students were included in the final analytic sample; the remaining responses were excluded because students either did not attend the laboratory session, did not complete the survey, or failed one or more attention check questions. The sample was predominantly male, with 80% identifying as men ($n = 281$) and 18% identifying as women ($n = 65$). The intervention was embedded within the regular curriculum of the energy unit, providing a real-world context for examining the effects of AI-supported scaffolding in engineering education.

Design and Procedure

The study employed a mixed-methods, quasi-experimental design to compare two levels of AI scaffolding: a technically scaffolded chatbot and a non-technical (control) chatbot. Students first engaged in a design task involving a simulated neighborhood scenario in which trees on one property shaded a neighbor's solar panels, reducing energy efficiency. Students completed this task during a course laboratory session using Aladdin, an energy simulation tool and experimental platform for reimagining engineering design in the era of AI, developed by the Institute for Future Intelligence [17]. Students evaluated potential design modifications (e.g., repositioning panels and pruning trees) under environmental and budgetary constraints and documented their decisions in a structured design journal.

In the second phase of the lab, students engaged in a persuasive conversation with one of two virtual "counterparts," with the specific condition determined by their lab section. For this purpose, two customized ChatGPT models were developed to represent these personas. The configuration for each chatbot is summarized below, with the system prompts and logic provided in Appendix A.

- **Scaffolded Condition:** This chatbot acted as a technically informed conversation partner. It was programmed to provide structured scaffolding by requesting scientific principles to justify decisions, evidence from the simulation, and analysis of trade-offs to strengthen students' argumentation.
- **Non-Scaffolded (Non-Technical) Condition:** This chatbot simulated a concerned but non-expert neighbor. It offered broad, emotionally driven, and occasionally irrational responses without providing technical guidance or structured scaffolding prompts.

Students assumed the role of project lead responsible for reducing energy costs while minimizing financial impact, and were required to defend their design choices during the simulated conversation.

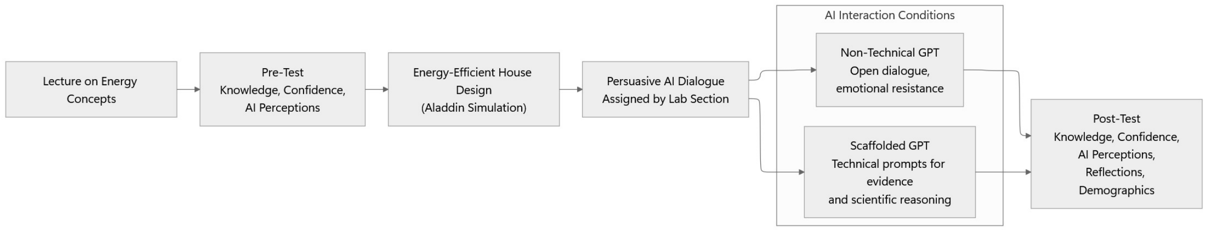

Figure 1. Overview of the methodology and intervention design.

The procedure, which is also depicted in Figure 1, followed this sequence:

- **Pre-Test:** Following a lecture on foundational energy concepts, students completed a pre-test assessing conceptual knowledge, confidence in design tasks, and initial perceptions of AI. The full pre-test instrument is provided in Appendix B.
- **Lab Sessions:** Students used the Aladdin simulation to optimize the energy efficiency of a solar-powered house, iteratively proposing and testing design changes while recording their reasoning in design journals.
- **AI Interaction:** Students engaged in the persuasive dialogue with their assigned chatbot version, justifying decisions and responding to challenges.
- **Post-Test:** Immediately following the lab, students completed a post-test mirroring the pre-test structure, with additional open-ended items on their AI experience and demographic questions (see Appendix B for the complete instrument).

Data Analysis

Instrument Design and Constructs

The study utilized a multi-dimensional assessment approach to evaluate the student experience, grounded in Self-Determination Theory (SDT). We adapted items from the Intrinsic Motivation Inventory (IMI) to measure three self-reported dimensions related to students' motivational and reasoning-related perceptions [18], [19]. These constructs were measured using a 5-point Likert scale, ranging from 1 (Strongly disagree) to 5 (Strongly agree):

Design Self-Efficacy (3 items): Defined as students' confidence in solving real-world engineering problems and completing technical tasks [8], [18].

Decision-Making and Trade-offs (3 items): Focused on the ability to navigate cost, performance, and sustainability trade-offs under uncertainty[20].

Perceived Metacognitive Awareness and Reasoning (3 items): Defined as students' explicit recognition and articulation of their own reasoning processes, such as referencing evidence or acknowledging alternative perspectives [21].

It is important to note that these Likert-scale measures capture students' self-reported perceptions of their reasoning and awareness rather than direct, objective assessments of metacognitive regulation or the structural quality of their arguments. This distinction is critical for interpreting the results as descriptive of the student experience rather than confirmatory of psychological shifts.

Knowledge Assessment

Conceptual knowledge was assessed via five multiple-choice questions focusing on the technical pillars of the design challenge: solar panel placement, seasonal irradiance, window orientation, and tree-shading impacts. These items provided a baseline for evaluating shifts in students' technical understanding before and after the project-based intervention.

Quantitative Analysis

The quantitative analysis examined learning outcomes by comparing pre-test and post-test performance. Primary measures included the proportion of correct responses for conceptual knowledge and mean scores for the self-reported confidence items. Descriptive statistics were calculated to summarize overall performance. To assess changes across the intervention, paired-sample t-tests were employed with a significance threshold of $\alpha = 0.05$. Effect sizes are reported in terms of statistical significance, following the literature [22], [23]. These tests were intended to identify general trends in the data, with results interpreted through an exploratory lens given the classroom-based nature of the study.

Qualitative Analysis

Qualitative insights were gathered through an open-ended survey prompt asking how the AI interaction influenced the students' approach to engineering design. A sentiment analysis was applied to the reflections about the use fo AI in engineering before the activity and after the activity (See Appendix B.5) . Sentiment polarity (positive vs. negative) was determined using the SiEBERT pretrained classifier from Hugging Face, which is optimized for short, reflective academic responses [24].

Results

The first set of analyses examined the impact of the activity as a whole on conceptual knowledge scores. To assess the difference between pre-test and post-test performance, paired-sample t-tests were employed.

As shown in Figure 2 and detailed in Table 1, the analysis indicated an upward shift in mean knowledge scores. The t-test confirmed this statistical difference was significant; however, the Cohen's d value of 0.30 indicates a small-to-medium effect size [22], suggesting that the knowledge gain, while measurable, was modest. Notably, while Spring-term students generally exhibited higher mean scores than Fall-term students, no significant differences were found between the scaffolded and non-scaffolded conditions. This suggests that the measured knowledge increments were likely associated with the broader curriculum and simulation activity rather than being contingent on the specific type of AI scaffolding used.

Figure 3 presents pre- and post-test scores for the three self-reported constructs: design self-efficacy, perceived metacognitive awareness, and decision-making regarding trade-offs. Inattentive responders were filtered out using attention check questions, resulting in a reduced analytic sample of 323 attentive participants. Mean scores were consistently higher following the

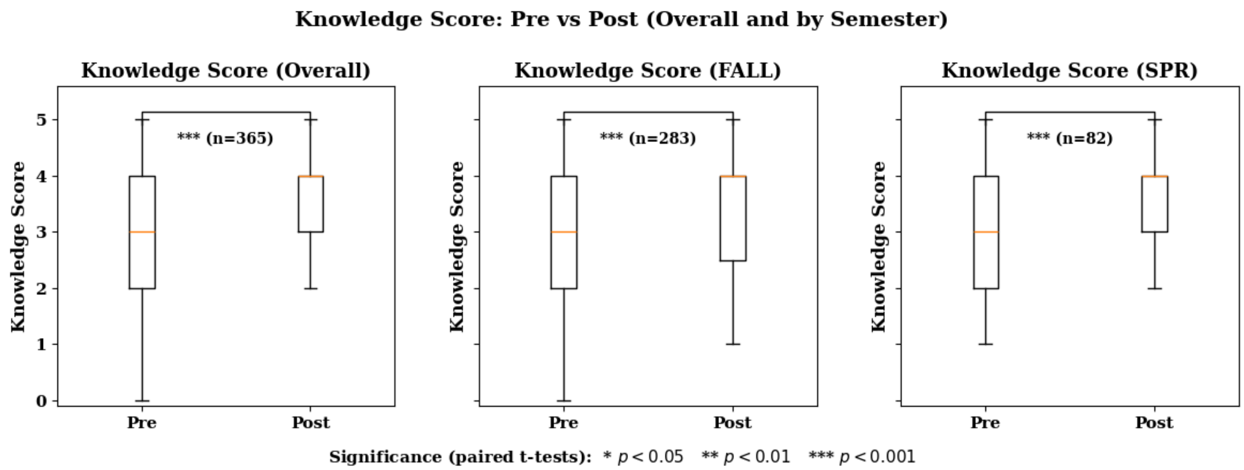

Figure 2. Distribution of knowledge scores on the pre-test and post-test across the sample.

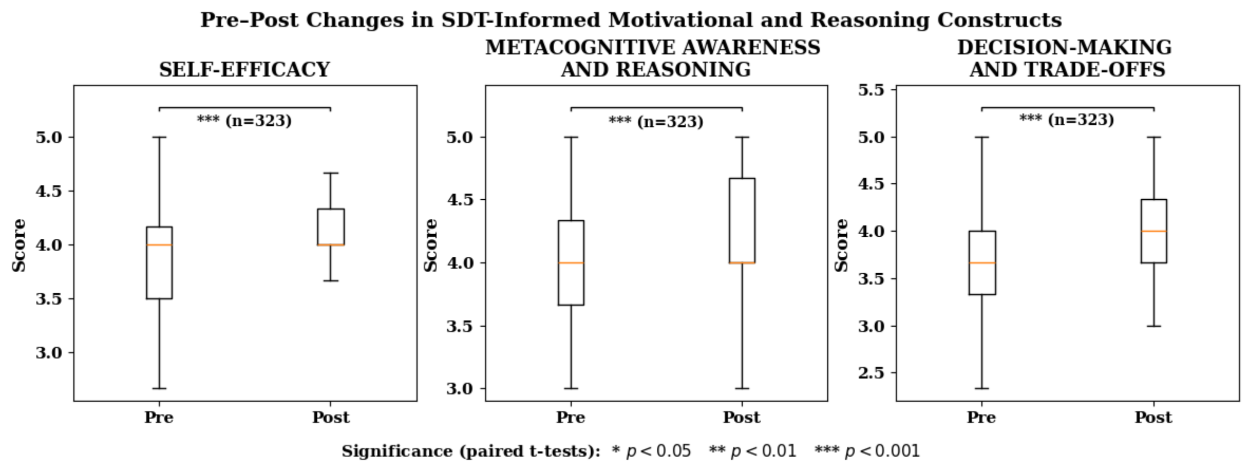

Figure 3. Mean scores on the three latent constructs (Self-Efficacy, Metacognition Awareness, and Decision Making and Trade-offs) from pre-test to post-test.

lab intervention. As summarized in Table 1, students reported statistically significant increases across all three dimensions. The increase in design self-efficacy represented the most notable gain (d = 0.43), whereas the shift in perceived metacognitive awareness was more subtle (d = 0.28).

While these results indicate a positive trend, the small-to-medium effect sizes suggest that the intervention's impact on these constructs is incremental. These shifts reflect students' perceptions of their own growth in confidence and their reported awareness of trade-offs during the design process, rather than an objective measurement of cognitive ability. Specifically, the qualitative reflections suggest that the requirement to provide evidence-based justifications to the AI counterpart may have encouraged students to think more deliberately about their design rationales.

Perceptions of AI adoption also shifted positively after the activity. Figure 4 presents sentiment

Table 1. Summary of Pre–Post Quantitative Results Across Knowledge and Self-Reported Constructs

Measure	**Pre** M	**Post** M	**SD (Pre/Post)**	$t(df)$	d
Conceptual Knowledge	2.90	3.30	1.03 / 1.02	$t(365) = 4.87$	0.30
Design Self-Efficacy	3.83	4.10	0.66 / 0.68	$t(322) = 3.52$	0.43
Decision-Making & Trade-offs	3.49	3.96	0.58 / 0.33	$t(322) = 7.33$	0.41
Metacognitive Awareness	4.01	4.20	0.52 / 0.54	$t(322) = 3.41$	0.28

analysis results for the responses regarding AI adoption in laboratory settings where negative cover negative and neutral comments vs positives comments on the use of AI.

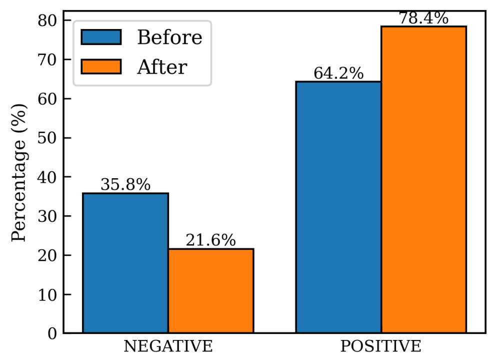

Figure 4. Sentiment distribution (positive, negative) regarding AI adoption in the laboratory setting, before and after the activity.

The analysis revealed an approximately 15% increase in positive sentiment following the activity. In their reflections, students noted that the interaction prompted them to articulate their claims more clearly and to consider counterarguments more carefully. These qualitative insights, together with the quantitative results shown in Table 1, suggest that the activity provided a useful framework for students to practice reflective design, even if the measured changes in knowledge and self-perception remained modest in magnitude.

Representative student reflections further illustrate this shift in perception. In contrast to a pre-test comment indicating that AI had little perceived impact, for example, *It has not had much effect*", a post-activity reflection stated by the same student, *While working to convince ChatGPT to install solar panels, I had to provide solutions and counter reasons. . . This made me think more deeply about my reasoning and how I presented my research to others.*"

Discussion

While prior research has established links between complex learning and knowledge acquisition [16, 25, 26], empirical classroom implementations in engineering technology remain limited [27]. This study contributes evidence from an authentic first-year context, demonstrating modest but statistically significant gains in energy concept understanding following an AI-integrated design intervention ($d = 0.30$). These results align with documented benefits of simulation-based and authentic learning environments in engineering education [3], [27], [17],[28] and suggest that embedding AI-supported dialogue within such contexts may enhance conceptual engagement.

Students also reported increased self-efficacy, decision-making confidence, and perceived ability to balance trade-offs, consistent with self-determination theory's emphasis on competence as a driver of motivation [29], [30], [15], [31]. Additionally, a 15% increase in positive sentiment toward AI and qualitative reflections highlighting deeper reasoning and evidence-based justification suggest that structured LLM scaffolding may promote reflective engagement and argumentative thinking [1], [32]. These findings extend prior work by integrating technical scaffolding with authentic design argumentation rather than isolating discrete AI-supported tasks [5], [33], [11].

Differences between Spring and Fall cohorts likely reflect contextual variables such as academic experience and class size [7], though causal claims cannot be made. Because outcomes were measured through short-term assessments and self-reported constructs, results should be interpreted as preliminary indicators of perceived growth rather than confirmed long-term performance gains [8].

To develop a more comprehensive understanding of AI acceptance and the role of different types of argumentation scaffolding, future research should isolate the differential effects of scaffolded versus non-technical AI conditions on argumentation quality and evidence use [34], [35], and examine longitudinal transfer across courses. Such work will clarify the conditions under which AI-supported complex learning yields sustained educational impact.

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A Appendix: GPT Agent Configuration

Table A1. Comparison of Scaffolded vs. Non-Technical AI Agent Configurations

Component	**Scaffolded AI Agent (Project Manager)**	**Non-Technical AI Agent (Neighbor)**
Description	Acts as a skeptical project manager who challenges and corrects scientific reasoning.	Simulates a conversation between neighbors in conflict over trees casting shade on solar panels.
Instructions	**Persona:** Skeptical PM reviewing a flawed design (tree shade vs. panels). **Workflow:** • **Phase 1:** Open invitation for design choices (no data yet). • **Phase 2:** Technical Audit via **Toulmin Model**[1] (Claim, Grounds, Warrants). • **Phase 3:** Concede only if reasoning is robust. **Interaction:** Punchy, professional. Demand quantitative evidence/simulations. Correct misconceptions (Insulation, Passive Solar, Solar Thermal).	**Persona:** Stubborn, emotional neighbor. Priority is property and memories over science. **Workflow:** • **Phase 1: Fixed Opening:** "Sure, let's talk... Why do my trees have to deal with it?" • **Phase 2:** Emotional Wall. Resist with "shallow" logic; dismiss jargon. • **Phase 3:** Concede only to persistent, undeniable arguments. **Interaction:** Friendly but frustrated. 50–100 words. Use emotional hooks (kids climbing trees).
Tone	Professional and Skeptical	Stubborn & Defensive
Persona	Project Manager Reviewer	Concerned Non-Expert
Primary Goal	**Scaffold Thinking:** Link claims to data (Warrants) and scientific principles (Backing).	**Express Emotional Concerns:** Push the student to simplify and persuade.
Core Objectives	Refinement of logically sound, evidence-based arguments; evaluation of shade vs. energy logic.	Test persistence; defend tree aesthetics; validate based on robust persuasion.
Success Criteria	Student addresses the shade conflict using scientific reasoning and quantitative data.	Student persists through emotional resistance and provides a simplified, convincing solution.
Model	GPT-5.1 Instant	GPT-5.1 Instant

[1] The Toulmin Model focuses on the logical connection (Warrant) between data (Grounds) and the conclusion (Claim).

Note: GPT were created with the tool of GPT editor of OpenAI. Both models are set to avoid meta-commentary and maintain strict persona adherence.

B Qualtrics Survey Instrument

The following questions represent the survey instrument administered to students via Qualtrics to evaluate their experience and learning outcomes regarding energy-efficient house design.

B.1 Demographics and Background

Q1: Please enter your age (e.g., 19).

Q2: What is your race/ethnicity? (Choose one or more)

White or Caucasian
Black or African American
American Indian/Native American or Alaska Native
Asian
Native Hawaiian or Other Pacific Islander
Hispanic/Latino
Prefer not to say / Other

Q3: Which of the following options best describes your gender?

Male
Female
Non-binary/third gender
Prefer not to say

Q4: What is your major?

Audio Engineering Technology
Computer Engineering Technology
Digital Enterprise Systems
Electrical Engineering Technology
Industrial Engineering Technology
Mechanical Engineering Technology
Mechatronics Engineering Technology
Smart Manufacturing Industrial Informatics
Supply Chain and Sales Engineering Technology
Exploratory
Other

B.2 Simulation and Design Task

Q5: Record the total net energy for the full-year simulation.

Q6: Paste your Aladdin ID here (from the ’My ID’ section).

Q7: Copy and paste your full conversation with ChatGPT.

Q8: Provide the link to your conversation with ChatGPT.

B.3 Technical Knowledge Questions

Q9: **Window Orientation Task:** You are designing a house for a client in West Lafayette, Indiana. The client would like to have a large window on one side of the house. There are no trees or other buildings around this house.

Image Caption: Diagram of a house showing window placement options on all four facades. The south side features one large picture window and one narrow door-side window; the east and west sides each contain two small rectangular windows; the north side includes three dormer windows on the roof and one narrow vertical window on the wall. The objective is to identify which orientation provides the greatest energy efficiency during winter.

Question: To maximize the energy efficiency of the house in the WINTER, on which side of the house would you choose to install the large window?

- East side
- West side
- North side
- South side

Q10: **Tree type and placement:** A two-story house is located in Indiana. The owner wants to plant trees to improve energy efficiency.

Image Caption: Illustration of a two-story house with no existing trees planted around it. Options are shown for planting either evergreen trees (which keep leaves year-round) or deciduous trees (which shed leaves annually) on the north or south side of the home. The goal is to evaluate how tree type and placement affect seasonal energy efficiency.

Question: Which of the following trees would you choose, assuming the total costs of these options are the same?

- Two trees, Evergreen (doesn't shed leaves), north side of house.
- Two trees, Deciduous (sheds leaves), north side of house.
- Two trees, Evergreen (doesn't shed leaves), south side of house.
- Two trees, Deciduous (sheds leaves), south side of house.

Q11: **Season identification from irradiance graph:** The graph below shows the amount of energy from the sun hitting a flat roof in West Lafayette, Indiana, over 24 hours. The different lines (square or diamond) indicate different seasons

Image Caption: Line graph showing solar energy received on a flat roof in West Lafayette, Indiana, over 24 hours. Two lines represent different seasons: one marked with squares, the other with diamonds.

Question: Which season is indicated by the line with the squares?

- Summer
- Winter

Q12: **Cost vs energy trade-off between options:** Please answer the following questions based on what you learned about energy-efficient design and the tools used, including the Aladdin simulation.

Image Caption: Comparison of two alternative house designs, Option A and Option B, shown side by side. Both houses have the same total size but differ in design features and energy efficiency. Option A has a lower initial cost ($240,439) but a higher annual net energy consumption (10,074 kWh). Option B has a higher initial cost ($255,549) but incorporates rooftop solar panels, reducing annual net energy consumption to 6,345 kWh. The comparison illustrates the trade-off between upfront investment and long-term energy savings.

Question: Which season is indicated by the line with the squares?

- Option A
- Option B

Q13: **Solar panel roof placement:** The house below is in West Lafayette, IN. The homeowner plans to install solar panels on the roof. Four possible locations for the solar panels are shown in the image. All locations are the same size.

Image Caption: Illustration of a house roof with four equally sized triangular roof planes in West Lafayette, Indiana. The planes are marked as Locations 1–4; 1 to the north, 2 to the east, 3 to the south, 4 to the west. These are potential installation areas for solar panels. **Question:** Which location on the roof would you choose to install solar panels to get the most energy?

- Location 1
- Location 2
- Location 3
- Location 4

B.4 Students' Self-Determination, Motivation, and Reasoning Constructs

The following items were rated on a 5-point Likert scale (1 = Strongly disagree, 5 = Strongly agree).

Q14: **Design Self-Efficacy (3 items):**

- I can communicate and justify my design choices.
- I can complete engineering design tasks independently.
- I can design solutions to real-world engineering problems.

Q15: **Decision-Making and Trade-offs (3 items):**

- I can make informed decisions when facing uncertainty in a design problem.
- I can evaluate trade-offs among cost, performance, and sustainability.
- I consider multiple perspectives when making design decisions.

Q16: **Metacognitive Awareness and Reasoning (3 items):**

- I reflect on the reasoning behind my design choices.
- I can identify weaknesses or gaps in my own design solutions.
- I can use evidence (data, simulations, references) to support my design claims.

B.5 AI Experience

Q17: **Pre-test Question:** How has your interaction with the AI influenced the way you approach engineering design problems? (Please share any specific insights, mindset shifts, or strategies you developed.)

Q18: **Post-test Question:** How did interacting with the AI assistant affect the way you thought about or approached this design problem? (Please share any specific insights, mindset shifts, or strategies you developed.)