Work in Progress: Learning by AI-Assisted Reverse Engineering (LARE) Using Aladdin

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Abstract

Reverse Engineering and design optimization are common engineering practices. However, integrating reverse engineering with generative artificial intelligence in a learning setting remains unexplored. Literature shows that reverse engineering activities enhance systems thinking, creativity, and technical communication in engineering disciplines. Recent advances in large language models (LLMs), such as ChatGPT, provide meaningful ways to facilitate reasoning and learning when properly guided. This paper introduces Learning by AI-Assisted Reverse Engineering (LARE), a proposed pedagogical framework that integrates reverse engineering with generative AI tools. The proposed idea is substantiated with an author-led pilot study using Aladdin software, a generative computer-aided design tool for building design simulation. Through a collaborative inquiry, we used Aladdin design software and LLMs to reverse-engineer a building design, analyze its energy efficiency through simulation, and optimize design variables. Our goal was to experientially and reflectively understand how engineering reasoning and literacy manifested as we engaged in AI-supported design. Results from simulation improvements and reflection data reveal conscious uses of LLMs in support of reasoning variables, energy optimization techniques, and reflection on generative artificial intelligence.

Introduction

The engineering practitioner is often confronted with existing designs, incomplete documentation, or opaque systems that need to be systematically investigated rather than designed from scratch. It is essential for engineers to have the ability to troubleshoot and reverse-engineer existing systems. Hence, engineering education must equip the learner not only with the skills necessary to develop new technology but also the skills necessary to investigate, assess, and enhance existing systems.

Reverse engineering is a type of design practice but also a teaching methodology that systematically takes the learner from the observable to the functional, from the artifact to the design logic [1]. In contrast to forward engineering methods that begin with abstract requirements and move towards implementation, reverse engineering starts with an examination of existing systems and aims for conceptual understanding, which promotes reverse and system-level thinking [2]. The reverse engineering pedagogy has been incorporated in engineering education in various ways to facilitate engineering communication, justification of designs, and creative problem-solving skills [3,4]. In conventional reverse engineering activities, there is a need for disassembly for the purpose of understanding. The goal for understanding an existing system or solution is highly applicable to the solutions generated by generative AI tools.

The applications of generative AI, in the form of large language models, are also increasingly being used in educational settings. These applications offer opportunities for explanation, ideation, and interpretation in new and innovative ways. However, unstructured applications of AI may foster passive learning and deemphasize cognitive engagement in engineering education [5].

While prior work has explored reverse engineering pedagogy and the use of LLMs in education independently, there is limited research on integrating these approaches into a structured learning framework. To address this gap, we introduce Learning by AI-Assisted Reverse Engineering (LARE), a pedagogical framework that combines reverse engineering processes with AI-supported reasoning We also examine how reverse engineering pedagogy can be intentionally integrated with AI tools to facilitate deeper levels of learning and reflection on the use of AI. By integrating engineering design, simulation-based reasoning, and AI literacy, this work focuses on engineering education, computational thinking, and responsible use of generative AI. Our research question is: *How can the concepts of reverse engineering be applied through the use of generative AI tools in order to facilitate engineering reasoning and literacy in AI?*

Literature Review

Reverse Engineering in Engineering Education

Reverse engineering has been applied across several engineering fields. In mechanical engineering, reverse-engineering-based disassembly exercises have contributed to improved component identification and system knowledge [6]. The combination of reverse engineering, computer-aided design modeling, and design graphics education has shown benefits in teamwork and technical communication skills [3]. Wood et al. further identified reverse engineering as essential in training students for open-ended capstone projects [1].

In electronics education, teaching approaches based on reverse engineering have focused on hardware analysis and vulnerability testing. Walendy et al. demonstrated the effects of Integrated Circuit and Printed Circuit Board reverse engineering, in which students confront the reality of the systems' limitations, including security [7]. The use of machine learning to automate the reverse engineering process, specifically for image segmentation of Integrated Circuits, was also explored [8].

In computing education, programming education with a reverse engineering approach has been shown to change the focus of student learning from code writing to logic interpretation and system understanding. Tan and Loo found a motivation and confidence boost among students, although they also emphasized challenges in abstraction and code-reading skills [9].

Robotics learning is another area that illustrates the relevance of revere engineering teaching. Zhong et al. found that reverse engineering enhanced creativity and self-efficacy in learning robotics [2]. Song et al. found increased engagement and interdisciplinary thinking in role-play activities related to reverse engineering [10].

Taken together, these studies suggest that teaching through reverse engineering facilitates learning by creating an interface between theory and practice. Nonetheless, challenges exist regarding scalability, knowledge transfer, and scaffolding.

Cognition and Motivation Foundations

Learning Science Research emphasizes the interplay among cognition, motivation, and self-regulation to achieve effective learning outcomes. According to Shuell, learning is a process of active knowledge construction [11]. The aspect of self-directed learning is critical for promoting autonomy and transfer, according to Boekaerts [12]. Motivation research indicates that persistence and engagement with learning outcomes depend on perceived competence and value [13].

Additionally, cognitive load affects engagement in cognitive tasks. Feldon et al. indicated that mental effort serves as a motivational cost [14]. The Cognitive-Affective-Motivation Model proposed by McGrew combines aspects of cognitive load theory with motivational theories [15]. The theories above underscore the importance of well-structured scaffolding in instruction that is moderately challenging. In this study, AI is positioned as a structured scaffold that supports cognitive engagement while helping learners manage complexity during engineering design tasks.

Large Language Models in Education

Recent research has shown that the learning process can be enhanced by intentional use of LLMs. This was demonstrated through the enhanced conceptual knowledge and computational thinking abilities displayed by the middle school participants using the LLM-based STEM activities developed by Guo et al. (2025) [16]. Frankford et al. also observed learning gains through AI tutoring systems [17].

However, there are also issues regarding the overutilization of AI results. In 2024, a study by Jošt et al. found that excessive reliance on code generated by AI was associated with reduced autonomous reasoning [5]. Another significant aspect worth noting is the need for explicit scaffolding when using ChatGPT in engineering problem-solving, as indicated by Wang et al.[18]. These findings highlight the importance of designing structured AI-supported learning environments that guide students toward critical engagement rather than passive dependence.

Despite these advances, existing work does not explicitly integrate reverse engineering workflows with generative AI as an interpretive scaffold. This gap motivates the development of the LARE framework.

Conceptual Framework

In the study, we propose learning by AI-Assisted Reverse Engineering (LARE) as a pedagogical approach that combines reverse engineering with the capabilities of generative AI. Reverse engineering is a top-down analytical approach that helps learners move from a system's observable behavior to its design logic [19].

The framework has five stages:

1. Observation
2. Functional inference
3. Inspection
4. Optimization

The process is aided by generative AI tools, which assist in the formulation and interpretation of simulation results and the generation of alternatives during the design process. Crucially, AI is situated as an interpretive scaffold rather than a decision-maker in its own right. Students are left with the task of interpreting AI results and making decisions during the final design process, which is crucial for maintaining critical engagement with AI tools in educational settings [18].

The process starts by observing an image or screenshot of a building that is to be reverse engineered, followed by the design of a building using Aladdin's built-in LLM function (See Figure 1).

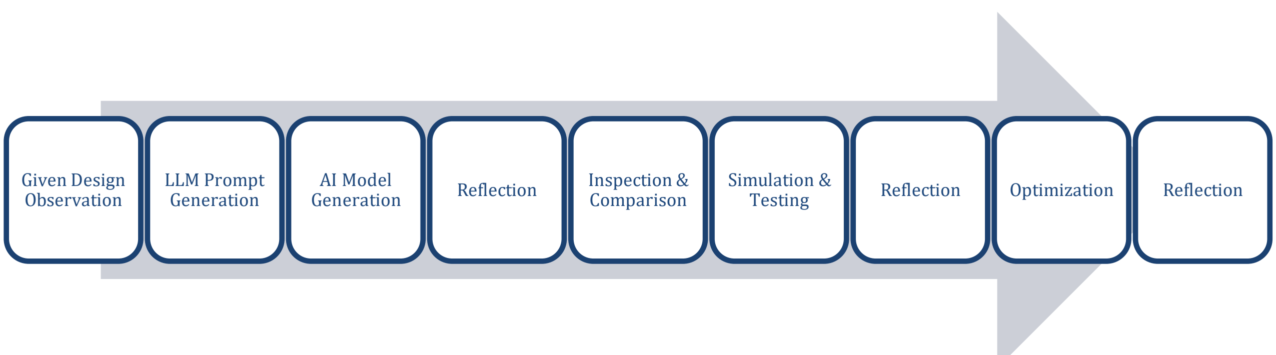


Figure 1. LARE: Learning by AI-Assisted Reverse Engineering process (Version 1)

The LARE framework operationalizes self-regulated learning through iterative goal setting, testing, and reflection; cognitive load through scaffolded reverse engineering rather than open-ended design from scratch; and motivation through visible performance feedback and studentdirected optimization. Reflection prompts are aligned with these constructs to support metacognitive monitoring and strategy adjustment.

Methods

The framework was implemented through a collaborative inquiry using Aladdin, a generative building design and simulation platform. Aladdin is an AI-supported building design environment that allows users to generate parametric 3D models from natural-language prompts and evaluate performance through built-in energy simulations. Users can inspect material properties (e.g., R-values, window U-values), modify design parameters manually, and run simulations to explore tradeoffs between energy efficiency, cost, and constraints.

Collaborative Inquiry

The activity engaged two authors in energy-efficient building design while learning to work effectively with AI tools. Collaborative and action-oriented research methods focus on problem formulation, shared understandings, and feedback, which have been observed to improve learning outcomes, relevance, and educational development [20]. Instead of implementing the activity as a rigid experimental design, the collaborative approach enables iterative refinement of scaffolds, reflection prompts, and AI supports in response to observed needs, while ensuring continued alignment with instructional objectives.

Existing literature on collaborative inquiry shows how deliberate collaboration triggers collective sensemaking and enhances learning by engaging in design cycles and examining evidence with a view to reflection [21]. This is very pertinent to AI-supported learning contexts, where unpredictable patterns may emerge in students' engagement with innovative tools. By engaging in this manner as facilitators and designers together, we have ensured that learners remain active as decision-makers in their critical analysis of AI-supported outcomes. In this manner, we have conducted our study, thereby enhancing the validity of this case study.

Activity Workflow

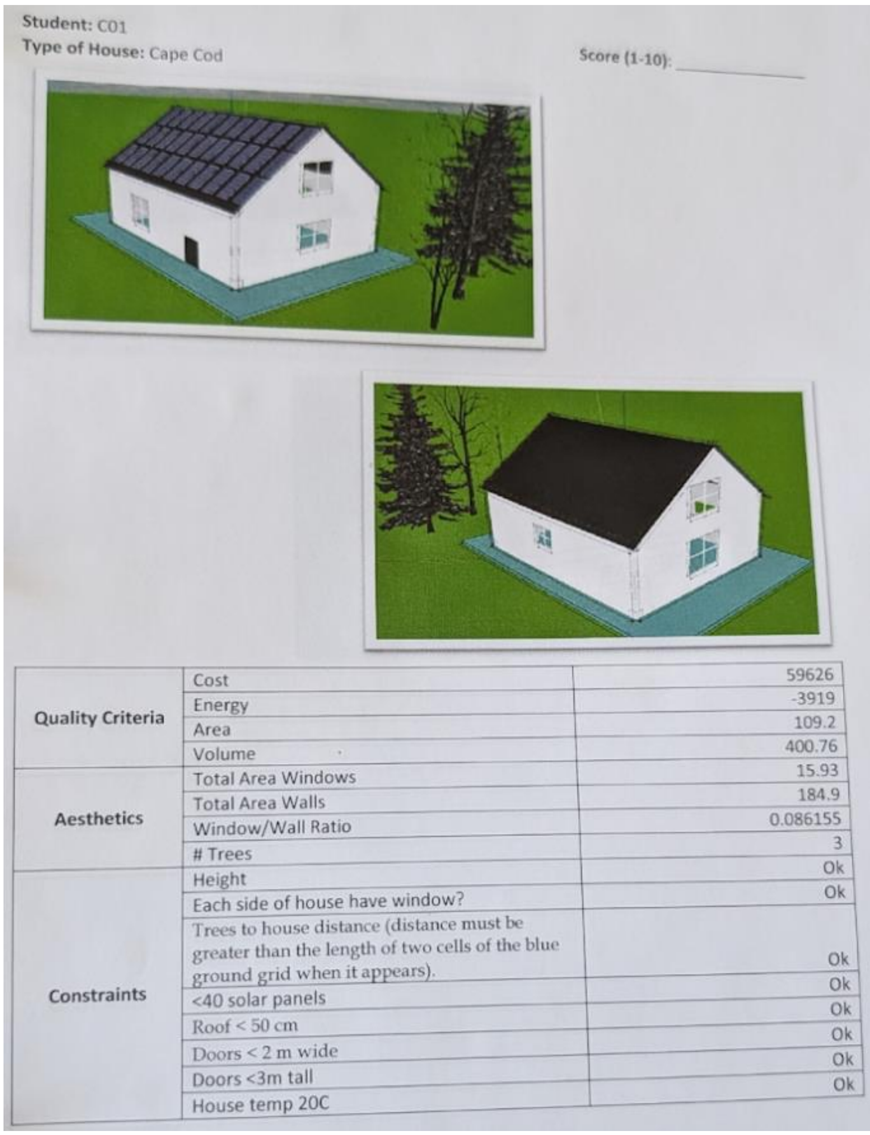
We conducted a collaborative pilot study of the proposed workflow to refine activity design and analytic procedures. Two conditions were explored: (1) an LLM-assisted design process and (2) a non-LLM design process. Both conditions were conducted by the authors to refine the instructional design. In the non-LLM condition, the design process was conducted without assistance from ChatGPT. Instead, parameter selection and design modifications were performed manually through trial-and-error and simulation feedback The classroom implementation with eighth-grade students is planned as future work. Unless otherwise noted, results reported in this section reflect the authors' pilot engagement rather than student data. Summarized in Table 1, we followed a structured LARE activity workflow aligned with reverse engineering pedagogy.

The study employed LARE process using AI, which tracked our design activity from observation of an artifact through simulation-based optimization and reflection. The exercise started with us being provided with a screenshot of a known design of a residential building, which was taken as the baseline artifact for reverse engineering (Figure 2). Figure 2 also includes performance metrics (e.g., cost, energy consumption, area, volume) generated by the Aladdin platform. These values serve as baseline indicators of design performance and inform subsequent reverse engineering and optimization decisions.

Table 1. LARE: Learning by AI-Assisted Reverse Engineering Activity Workflow

Step	Our Action	Our Purpose
1. Given Design Observation	Studied a screenshot of an existing building (created previously by an 8th-grade student or an expert designer).	Establish a baseline design to reverse-engineering.
2. Description of Design Features	Listed visible attributes (shape, roof, wall, window layout, material, colors, etc.).	Identify design elements for reconstruction.
3. LLM-Assisted Prompt Generation	Asked an LLM to convert their description into a detailed Aladdin prompt.	Learn how AI converts human language into instructions.
4. AI Model Generation (Aladdin)	Entered the prompt into Aladdin to generate a building model.	Observe AI interpretation and assumptions.
5. Inspection and Comparison	Compared the AI-generated model to the screenshot, identifying matches and differences.	Reverse-engineer the AI design logic.
6. Simulation and Testing	Simulated performance (temperature, sunlight, location, cost, etc.).	Evaluate whether the design meets performance goals.
7. Revision and Optimization	Refined the prompt or manually modify parameters to improve results.	Iterative design improvement via human and AI reasoning.
8. Reflections	Reflected on engineering decisions and AI reasoning.	Connect learning outcomes to practice.

We chose to record visible characteristics such as building shape, roof, windows, solar panels, and environmental factors. This created a common ground that would later be useful in the reconstruction process. This was the part of the process where we had the opportunity to make assumptions about unknown variables. Based on this observation, we used ChatGPT to translate visual design elements into a written prompt suitable for use on the Aladdin platform as shown in Figure 3. We began with an informal description of the building and asked the AI to rewrite it as a prompt with style, geometry, and performance-based parameters. Through iterative design processes, we varied the specificity of the prompt parameters by including additional information, such as window numbers, roof type, and solar panel placement.



Student: C01
Type of House: Cape Cod
Score (1-10): ____________

Quality Criteria	Cost	59626
	Energy	-3919
	Area	109.2
	Volume	400.76
Aesthetics	Total Area Windows	15.93
	Total Area Walls	184.9
	Window/Wall Ratio	0.086155
	# Trees	3
Constraints	Height	Ok
	Each side of house have window?	Ok
	Trees to house distance (distance must be greater than the length of two cells of the blue ground grid when it appears).	Ok
	<40 solar panels	Ok
	Roof < 50 cm	Ok
	Doors < 2 m wide	Ok
	Doors <3m tall	Ok
	House temp 20C	Ok

Figure 2: Screenshot of an Existing Building Design

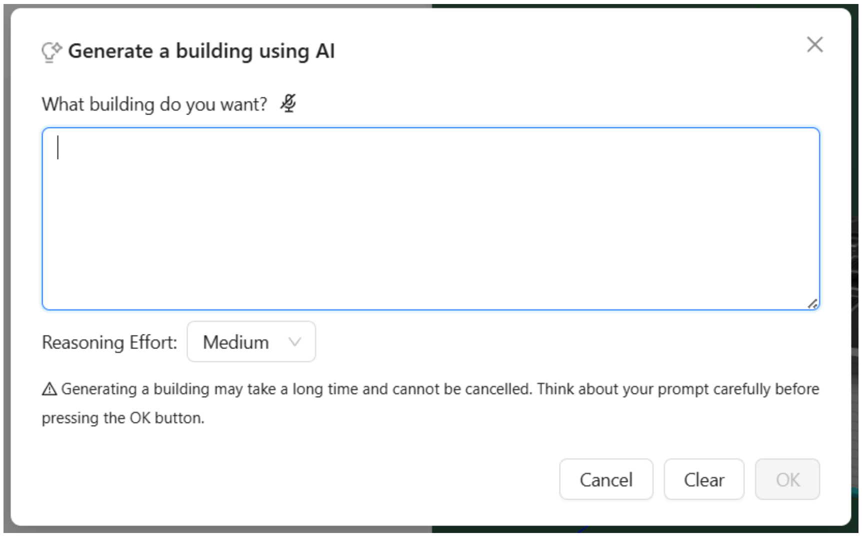


Figure 3: Building using AI in Aladdin

This refined task was then introduced into the Aladdin system, which produced a three-dimensional parametric building model based on geometric, thermal, and material considerations. This result served as the reconstructed form of the actual design, which was used as a reference for the analysis. It was at this level that we viewed the model created by the AI system as a system that was completed and now needs to be examined and validated. (Figure 4).

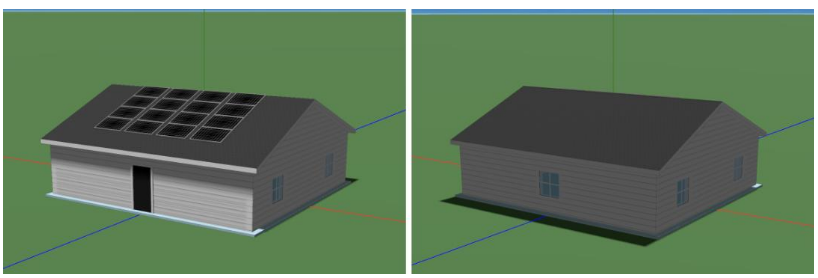


Figure 4: Aladdin AI Generated Model with ChatGPT

We further contrasted the created AI model with the original screenshot reference image. Analyzing this contrast revealed both convergences and divergences between the model specified in the problem set and the AI's output. Although some convergences in building structure and roofing were achieved as expected, some divergences in window arrangement, solar cell placement, tree placement, and material selection were observed. Through documentation, we drew inferences from the created parameters to deduce assumptions in AI about model symmetry, energy model priorities, and simplifications and adjustments for aesthetic and user-friendly aspects (Figure 5).

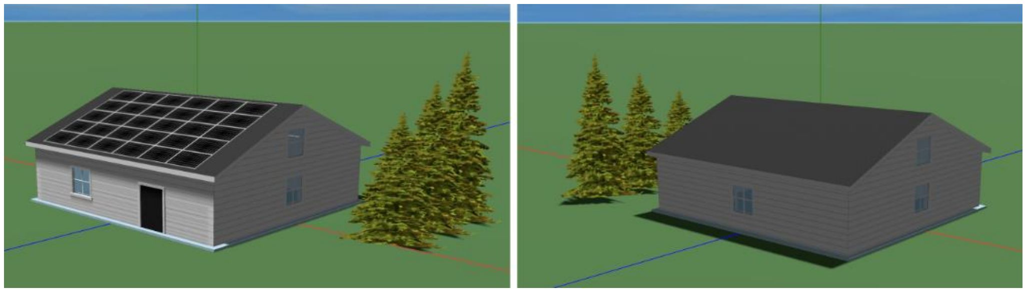


Figure 5: Author Modified Model

To analyze the performance effects, we carried out energy simulations with Aladdin under default conditions. Simulation results were obtained for heating demand (Figure 6), solar power contribution (Figure 7), and overall net annual energy balance. Instead of focusing on absolute performance, we explored the effects of various parameters on energy use and realized that heating demand was a significant load factor, and that factors such as quality and windows also have specific effects on it.

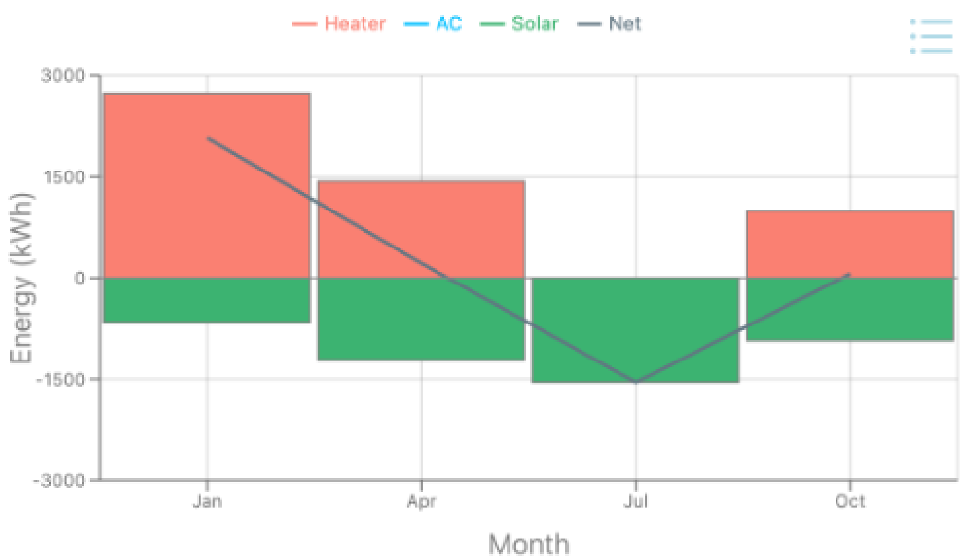


Figure 6: Yearly Building Energy Profile of LLM Assisted Design (Design 1)

[Heater= 10185kwh, AC=0, Solar Panel=15233kwh, Net=: -5048kwh]

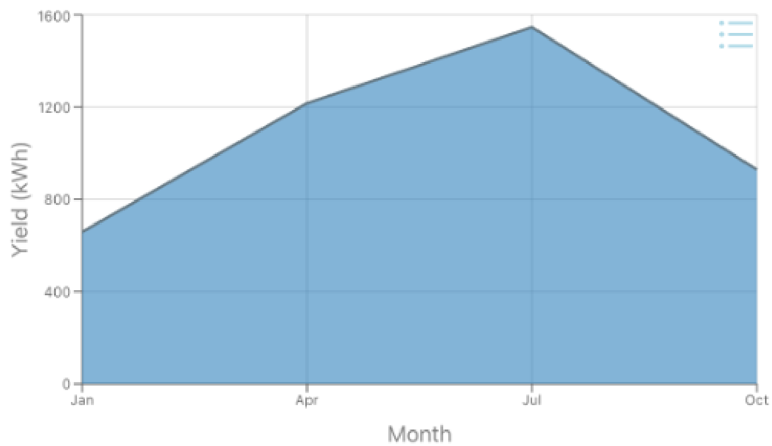


Figure 7: Solar Panel Yearly Yield Profile of LLM Assisted Design (Design 1)

[Yearly Total= 15233.66 kwh, Module Count= 35, Mean Yield=435.25 kwh, Total Cost=$1916.25, Total Revenue=$3808.42, Profit=$1892.17]

Based on the simulation results, we continued refining their design using a set of chosen parameters. ChatGPT was used again to assist with analyzing simulation graph outputs and extracting meaning from energy performance indicators. Using an understanding of how these outputs function, we varied a set of parameters for our design, including solar panels and boundaries, with a gradual aim towards enhancing overall design performance.

Design Criteria

We optimized designs using both aesthetic and performance criteria. Performance goals included minimizing energy consumption, maintaining comfortable indoor temperature, optimizing window-to-wall ratios, and reducing overall building cost. We selected which criteria to prioritize based on design goals (Table 2).

Table 2: Design Evaluation Criteria Used in LARE Activity

Aesthetic / Structural Criteria	**Performance Criteria**
• Style consistency (e.g., modern, colonial) • Material and color choices are appropriate for the context • Maintain building size within constraints • Minimum required number of trees + safe tree distance	• Minimize energy consumption (kWh ↓) • Maintain a comfortable indoor temperature • Optimize window-to-wall ratio (~50% where possible) • Reduce overall building cost

Results

The results presented here are based on an author-led pilot. Design 1 refers to the LLM-assisted design process, while Design 2 refers to the non-LLM design process. These results are intended to demonstrate feasibility rather than evaluate student learning outcomes.

Learning Outcomes

This study showcased two complementary sets of learning outcomes as shown in Table 3.

Table 3: Engineering and AI Learning Outcomes

Engineering Learning Outcomes	AI Learning Outcomes
• Identified the design features that influence energy efficiency and cost. • Analyzed the relationships among materials, insulation, climate, and building comfort. • Used simulation data to justify design decisions. • Applied iterative improvement rather than trial-and-error guessing.	• Explained how generative AI interprets and transforms human input (prompts → design choices). • Compared the effects of small prompt variations on model outcomes. • Recognized where AI makes reasonable assumptions and where human judgment is required. • Used AI as a partner for reasoning rather than a tool for quick answers.

Performance Improvements with LLM Support

Simulation results demonstrated substantial performance gains for design 1 but not for design 2 following LLM-assisted optimization (Table 4).

Table 4: Building Energy Performance Comparison

Metric	Initial Design	Optimized Design 1	Optimized Design 2
Heating Energy needed(kWh)	15,464	10,185	14,397
Solar Generation (kWh)	13,057	15,233	12,424
Annual Net Energy (kWh)	+2,406	–5,048	+1,973
Number of Solar Panels	30	35	34
Annual Profit ($)	1,621.86	1,892.17	1,244.54

Reflection Data: LLM vs Non-LLM Conditions

Qualitative reflections revealed differences between the LLM-supported and non-LLM conditions. For example, when using LLMs, one observed that it improved their understanding of parameter interactions and energy optimization techniques. An author commented that AI "expanded my thought process with so many parameters that I have never thought of and how it interacted towards energy efficiency," making it clear how the parameters interacted with respect to energy efficiency. We also learned how to critique AI results rather than just trust them.

When using the non-LLM approach, trial-and-error learning dominated. While the AI-generated initial designs proved helpful, the amount of conceptual learning regarding AI reasoning and parameter interpretation was low (Table 5). When using the LLM, one of the author found it difficult to formulate the problem statement but remained motivated during the learning of the design process.

Table 5: Reflection themes

Category	Alladin with ChatGPT	Alladin without ChatGPT
Parameter Understanding	Improved first principle reasoning	Improved experiential learning
Optimization Strategy	Improved structural and performance criteria	Improving structural and visual criteria
Motivation Pattern	Initially overwhelming → stabilized over time	Consistent moderate

Discussion

These findings are based on an author-led pilot and should be interpreted as exploratory. The results indicate that LARE is beneficial in both cognitive and motivational aspects. Existing artifacts made entry easier and maintained complexity. AI-assisted simulation helped with rapid hypothesis testing. Notably, open-ended reflection questions encouraged critical assessment of AI responses, echoing suggestions from existing literature on effectively incorporating AI [5,18]. Open-ended reflection questions facilitate the development of new literacy in AI by addressing sensitivity in prompt design, limitations in interpreting AI outputs, and the role of human judgment. This work does not explicitly examine ethical or intellectual property considerations associated with reverse engineering and AI-generated designs.

Limitations

There are some limitations to the research work being presented in this paper. First, it must be noted that the availability of the original building models for the initial phase of the research was limited. In some cases, only screenshots of the former designs were available. Second, the proposed approach is demonstrated using a single AI-enabled design tool, Aladdin. While the framework is intended to be tool-agnostic, findings and design decisions are grounded in the functions and constraints of this platform. Third, the study design has not yet been deployed in a classroom setting. As a result, learning outcomes are intended rather than empirically measured.

Conclusion and Future Work

Future studies will pilot-test and refine the LARE framework through collaborative inquiry before large-scale deployment in a classroom setting. Testing in small collaborative groups helps instructors and researchers to identify usability challenges, modify scaffolding strategies, and refine activity designs based on formative feedback. This practice enables iterative improvement with minimal instructional risks during full deployment.

The LARE will be further developed by emphasizing systematic design reasoning while lessening reliance on trial-and-error approaches. By integrating structured prompting and reverse-engineering workflows, LARE fosters a culture of goal-driven exploration and informed decision-making. Future studies will investigate learning outcomes and design efficiency across a wide range of engineering contexts to establish its scalability and long-term instructional impact.

Future research will involve implementing and empirically evaluating the proposed study design at the classroom level. The proposed studies will include implementing the activity with middle school students to examine outcomes related to engineering design reasoning, motivation, and self-regulation, as well as addressing responsible AI use, authorship, and intellectual property awareness. Other studies will examine the impact of differences in initial models (e.g., peer-designed versus expert-designed) on engagement and learning. Future research may also investigate the transferability of the AI-supported reverse engineering framework to other domains, tools, and age groups, as well as the development of assessment instruments to capture better how students learn to work critically and productively with generative AI.

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