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AI-Powered Collaborative Simulation Learning for Electronic Manufacturing Education

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Abstract

The increasing adoption of artificial intelligence (AI) and intelligent manufacturing technologies is reshaping the competencies required of engineers, particularly in electronics packaging, where thermal management, mechanical reliability, and design for manufacturability (DFM) must be addressed concurrently. Yet, engineering curricula often treat these domains in isolation and provide limited guidance on how AI can be integrated to support engineering reasoning. This paper presents an AI-powered collaborative simulation learning framework implemented in an undergraduate Electronics Packaging Applications course. The framework follows an enhanced flipped classroom model that integrates AI-assisted self-learning before class, AI-supported collaborative design during class, and simulation-based individual reflection after class. AI tools were introduced as instructional scaffolds for preparation, discussion facilitation, and reflective documentation, while course content, learning objectives, and assessment structures remained unchanged. The framework was implemented and iteratively refined over three consecutive semesters (n = 66 students). A mixed-methods assessment combined rubric-based evaluation of simulation accuracy, manufacturability reasoning, and technical communication with qualitative analysis of student reflections. Results show consistent improvement trends across semesters, with the strongest gains in students' ability to justify design decisions under manufacturing and reliability constraints. Students reported perceiving AI as a cognitive and organizational support rather than an answer generator. These findings suggest that intentional AI integration within a flipped, simulation-intensive course can support manufacturability-aware reasoning and reflective design practice. The proposed framework aligns with ABET student outcomes and offers a feasible model for AI integration in engineering education aligned with Industry 5.0.

Keywords: Artificial Intelligence, Electronics Packaging Education, Flipped Classroom, Design for Manufacturability

1. Introduction

1.1 The Changing Landscape of Engineering Education

The global manufacturing sector is undergoing a significant transformation driven by the emergence of Industry 5.0, which emphasizes human-centered automation, sustainability, and intelligent human–machine collaboration [1]. In contemporary electronic manufacturing, engineers are increasingly required to integrate multidisciplinary considerations, including thermal management, mechanical reliability, vibration behavior, and design for manufacturability (DFM) [2]. These demands reflect a shift away from isolated technical optimization toward holistic, decision-oriented engineering practice grounded in manufacturing realities.

Despite these evolving expectations, engineering education has not fully kept pace. Many undergraduate curricula continue to present thermal analysis, mechanical design, and computer-aided modeling as largely independent topics, often disconnected from manufacturability considerations. As a result, students may develop strong analytical skills yet lack experience synthesizing simulation results into defensible, manufacturable design decisions [3, 4]. This gap is particularly evident in simulation-intensive courses, where numerical results are often emphasized over engineering judgment and design justification.

1.2 Fragmented Learning Experiences in Simulation-Centered Instruction

In simulation-centered engineering courses, instruction frequently emphasizes analytical correctness and software execution while providing limited support for integrating results into broader design decisions. In electronics packaging education, students typically encounter thermal analysis, mechanical or vibration analysis, and CAD modeling as separate tasks, often completed through isolated assignments or laboratory exercises [5,6].

Consequently, while students may demonstrate proficiency in configuring simulations and interpreting numerical outputs, they often struggle to connect these results to manufacturability and reliability considerations. Design activities frequently conclude with performance validation rather than extending to trade-off analysis involving material selection, fabrication feasibility, and production constraints [7,8]. This compartmentalized learning experience limits students' ability to understand how multiple analyses collectively inform real-world engineering decisions.

At the same time, artificial intelligence (AI) tools are becoming increasingly accessible to students, yet their use in coursework is often informal and unstructured. Without clear pedagogical guidance, AI is frequently used for procedural assistance or explanation retrieval rather than for supporting reflective reasoning and design justification [9, 10]. This disconnect contributes to a learning environment in which analytical tasks are completed efficiently, but integrative reasoning remains underdeveloped.

Figure 1 illustrates this contrast by highlighting the shift from traditional simulation-centered instruction, which emphasizes isolated analytical competencies, to Industry 5.0–aligned engineering expectations that require integrated reasoning across thermal performance, mechanical reliability, and manufacturability, supported by human-centered AI (operationalized in this study as manufacturability reasoning).

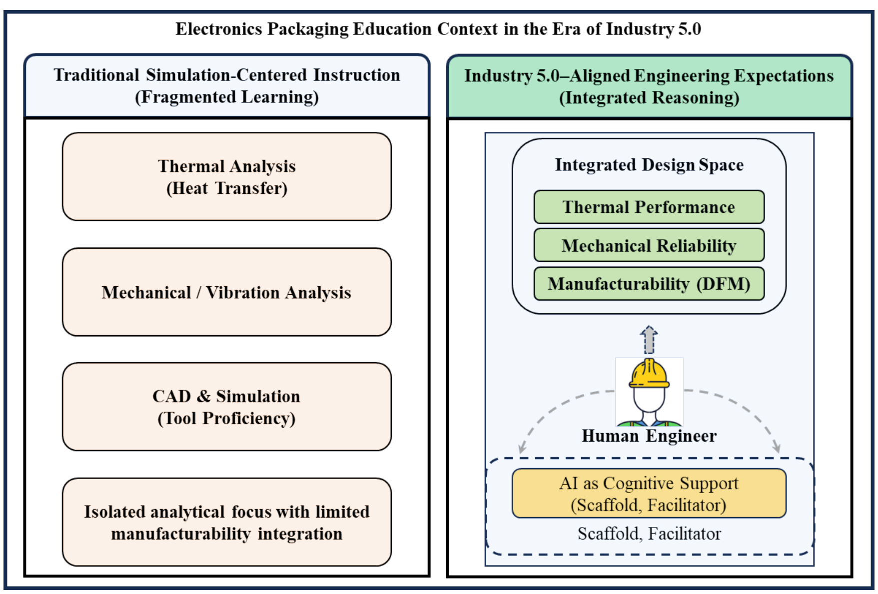

Figure 1: Conceptual contrast between traditional simulation-centered electronics packaging instruction and Industry 5.0–aligned educational expectations.

1.3 Opportunity for Human-Centered AI Integration

The convergence of AI and advanced manufacturing presents an opportunity to rethink simulation-based engineering education. When intentionally integrated, AI can function as a cognitive scaffold that supports self-regulated learning, facilitates collaborative reasoning, and encourages reflection on complex design trade-offs [11, 12]. Rather than serving as an automated solution provider, AI can help students organize ideas, surface assumptions, and articulate design rationale.

Flipped classroom pedagogies provide a natural structure for such integration. By shifting foundational content acquisition outside the classroom and reserving in-class time for higher-order activities such as discussion, design evaluation, and problem solving, flipped learning enables deeper engagement with complex engineering tasks [13]. Within this structure, AI can extend learning across preparation, collaboration, and reflection phases while preserving the central role of human judgment—an approach aligned with the human-centric principles of Industry 5.0.

1.4 Purpose and Research Questions

Motivated by these challenges and opportunities, this study examines how structured integration of AI within a flipped, simulation-intensive course can support student learning in electronics packaging education. Rather than treating AI as a standalone technological tool, the study focuses on its role as an instructional scaffold embedded within an existing course structure.

The study addresses the following research questions:

- RQ1: How does an AI-enhanced flipped learning approach influence students' simulation accuracy, manufacturability reasoning, and technical communication in an electronics packaging course?
- RQ2: How do students perceive the role of AI when it is embedded as a collaborative and reflective learning scaffold within simulation-centered design activities?

To distinguish this work from prior studies, the main contributions of this paper are as follows:

(1) An integrated instructional framework that combines AI-assisted pre-class learning, AI-supported in-class collaboration, and simulation-based post-class reflection within a flipped classroom structure;

(2) A focus on manufacturability reasoning as a central learning outcome in simulation-based engineering education;

(3) Longitudinal empirical evidence collected across three semesters using a mixed-methods assessment approach;

(4) A human-centered model of AI integration, positioning AI as a cognitive scaffold that supports reasoning and justification rather than as an automated solution generator.

By addressing these contributions, this study provides both empirical evidence and practical guidance for integrating AI into engineering education in ways that strengthen design reasoning, manufacturability awareness, and reflective practice. The following section situates this work within existing literature on AI in engineering education, flipped learning, and simulation-based instruction.

2. Literature Background and Theoretical Positioning

Building on the problem context outlined in Section 1, this section situates the study within three intersecting areas of research: (1) AI integration in engineering education, (2) flipped and collaborative learning, and (3) simulation-based instruction with an emphasis on design for manufacturability. These strands provide the foundation for identifying the research gap addressed in this work.

2.1 AI Integration in Engineering Education

Artificial intelligence (AI) has evolved from a supplementary instructional tool into a potential cognitive partner in engineering education. Early applications primarily focused on automated assessment, adaptive quizzes, and rule-based tutoring systems designed to support procedural learning [14]. More recent developments in large language models (LLMs) and generative AI have expanded this role to include higher-order tasks such as idea generation, design reflection, and technical communication [15,16].

A key insight emerging from recent studies is that the educational value of AI depends on how it is integrated pedagogically. When embedded within structured learning environments, AI can enhance self-regulation, conceptual understanding, and confidence in open-ended problem solving [17, 18].

In contrast, unstructured or ad hoc use of AI may lead to superficial engagement or overreliance, potentially limiting deeper learning and creative reasoning [19]. This dual potential has led to increasing emphasis on positioning AI as a cognitive scaffold that supports, rather than replaces, human reasoning [20].

In parallel, the concept of AI literacy has gained attention as an essential competency for engineering students. AI literacy involves the ability to critically interpret, evaluate, and appropriately use AI-generated outputs, particularly in contexts involving uncertainty and data-driven decision making [21, 22].

Developing such competencies is increasingly important for preparing students for environments characterized by characterized by human–AI collaboration and intelligent manufacturing systems. [23].

2.2 Flipped Learning and Collaborative Pedagogy

The flipped classroom model is widely used in STEM education to shift foundational learning outside the classroom and emphasize in-class problem solving and application [24, 25].

Recent research has extended the flipped paradigm through the integration of AI-supported collaborative learning environments. In such settings, AI tools can act as mediating supports by summarizing discussions, generating prompts, and providing formative feedback aligned with higher-order cognitive tasks [26]. These capabilities can enhance group interaction, promote balanced participation, and sustain engagement during complex design activities [27].

From a theoretical perspective, flipped and collaborative learning approaches are grounded in constructivist principles, emphasizing knowledge construction through interaction, reflection, and guided exploration. This alignment makes them particularly suitable for engineering education, where problem solving is inherently iterative, interdisciplinary, and team-based. Integrating AI within such frameworks presents an opportunity to further support collaborative reasoning and reflective learning processes.

2.3 Simulation-Based Learning and Design for Manufacturability

Simulation-based learning plays a central role in engineering education by enabling students to analyze complex systems and explore design alternatives in controlled environments. In electronics packaging, simulation tools are commonly used to study thermal behavior, mechanical stress, vibration, and reliability of assemblies [28]. These approaches support the development of analytical skills and conceptual understanding.

However, prior studies on simulation-based instruction primarily emphasize numerical accuracy and model configuration, with comparatively less attention to how simulation outcomes are linked to manufacturing feasibility and design decision-making.

Design for Manufacturability (DFM) addresses this gap by emphasizing the translation of digital designs into feasible, cost-effective, and reliable products [29]. Despite its importance in industry, DFM remains underrepresented in many undergraduate curricula, where design and manufacturing are frequently treated as separate domains [30]. This separation can limit students' ability to integrate analytical results into practical engineering decision making.

Recent advances in AI-driven manufacturing analysis tools offer new opportunities to bridge this gap. When combined with simulation workflows, AI can support evaluation of manufacturability, process feasibility, and design trade-offs across multiple domains. In electronics packaging, where thermal, mechanical, and production considerations are tightly coupled, such integration has the potential to support more holistic and realistic design reasoning.

2.4. Research Gap and Contribution

Although prior research has examined AI in engineering education, flipped learning, and simulation-based instruction, these areas have largely developed independently. Existing studies on AI-assisted learning often focus on tutoring, feedback, or content generation, while flipped learning research emphasizes engagement and participation. Similarly, simulation-based education tends to prioritize analytical accuracy without sufficient attention to how results inform manufacturable design decisions.

As a result, there is limited research on how these approaches can be systematically integrated to support higher-order engineering reasoning in manufacturing-aware design contexts. In particular, few studies examine how AI can be intentionally embedded across pre-class preparation, in-class collaboration, and post-class reflection to support the synthesis of simulation results into design justification grounded in manufacturing constraints. Furthermore, longitudinal evidence evaluating such integrated frameworks within a consistent course context remains scarce.

This study addresses these gaps by proposing and evaluating an AI-powered collaborative simulation learning framework implemented in an undergraduate electronics packaging course. The framework integrates:

- AI-assisted self-learning prior to class;
- AI-supported collaborative design during class;
- Simulation-based individual reflection following class activities.

Rather than positioning AI as an automated solution generator, the framework integrates AI to support reasoning, synthesis, and justification. Using a mixed-methods approach across multiple semesters, this study provides empirical evidence on how structured AI integration can influence simulation accuracy, manufacturability reasoning, and technical communication.

Table 1 summarizes the scope of prior work and highlights the limited overlap among AI integration, flipped learning, simulation-based instruction, and manufacturability-focused education, thereby motivating the need for the proposed integrated framework.

Table 1: Summary of prior work in AI, flipped learning, and manufacturability education

Study Focus	AI Integration	Flipped / Collaborative Learning	Simulation-Based Design	Manufacturability Emphasis
AI in Engineering Education	Yes	No	No	No
Flipped Engineering Courses	No	Yes	Yes	No
Simulation-Based Learning	No	No	Yes	No
DFM in Engineering Education	No	No	Yes	Yes
This Study	Yes	Yes	Yes	Yes

3. Methods

3.1 Course Context and Participants

3.1.1 Course Setting and Instructional Context

The proposed AI-powered collaborative simulation framework was implemented in an undergraduate Electronics Packaging Applications course offered within a Mechanical Engineering Technology program at a public institution in the United States. The course is a required upper-level offering with a combined lecture–laboratory format, designed to introduce students to the thermal, mechanical, vibration, and reliability considerations involved in electronic packaging design.

The course emphasizes simulation-based analysis using industry-standard computer-aided design and engineering tools. Across a 15-week semester, students engage in progressively complex topics including heat transfer, thermal stress, vibration, shock, and reliability analysis of electronic assemblies. Laboratory activities are closely aligned with lecture content and focus on applying analytical concepts through virtual experimentation and simulation. Course learning outcomes prioritize the integration of analytical reasoning, simulation proficiency, and engineering judgment in realistic design contexts.

Importantly, the formal course structure, learning objectives, and assessment scheme remained consistent throughout the study period. The AI-powered framework was introduced as an instructional enhancement layered onto the existing course design, ensuring alignment with departmental curriculum requirements and institutional academic integrity policies. Table 2 summarizes the core instructional components and delivery modes of the Electronics Packaging Applications course.

Table 2: Course structure and learning components

Component	Description	Delivery Mode
Lecture Content	Thermal management, mechanical reliability, vibration, and packaging principles	In-person
Laboratory Activities	Simulation-based analysis using CAD/CAE tools	In-person
Pre-Class Preparation	Concept review and question generation supported by AI tools	Individual
In-Class Activities	Team-based discussion and design evaluation	Collaborative
Post-Class Work	Simulation refinement and technical reporting	Individual

3.1.2 Participants and Enrollment

The framework was implemented over three consecutive semesters, with enrollments of 23, 21, and 22 students, respectively, resulting in a total of 66 participants. Students were primarily junior- and senior-level undergraduates majoring in Mechanical Engineering Technology or closely related engineering technology programs. Participant demographics and implementation consistency across semesters are summarized in Table 3.

Most participants had prior exposure to fundamental engineering analysis and computer-aided design tools through prerequisite coursework. However, few had formal experience integrating simulation results with manufacturability considerations or engaging in collaborative, open-ended design decision making. Similarly, while students were generally familiar with digital learning technologies, structured use of AI tools for engineering reasoning and reflection was new to the majority of participants.

Table 3: Participant overview and semester implementation

Semester	Enrollment	Academic Level	Course Format	AI Integration Consistency
Fall 2024	23	Junior/Senior	Lecture + Lab	Identical
Spring 2025	21	Junior/Senior	Lecture + Lab	Identical
Fall 2025	22	Junior/Senior	Lecture + Lab	Identical

3.1.3 Role of AI within the Course

AI tools were incorporated as instructional scaffolds rather than as required technologies or graded deliverables. Their use was guided by clearly defined learning objectives aligned with preparation, collaboration, and reflection. AI-generated outputs were not accepted as final answers, and students were explicitly instructed to evaluate, critique, and refine AI-assisted suggestions using engineering principles.

By positioning AI as a facilitator of learning rather than an authority, the instructional approach emphasized accountability, ethical use, and human-centered reasoning. This design choice ensured that AI integration supported, rather than disrupted, the course's existing emphasis on simulation accuracy, manufacturability reasoning, and technical communication. Figure 2 illustrates the scope of AI integration within the existing course structure.

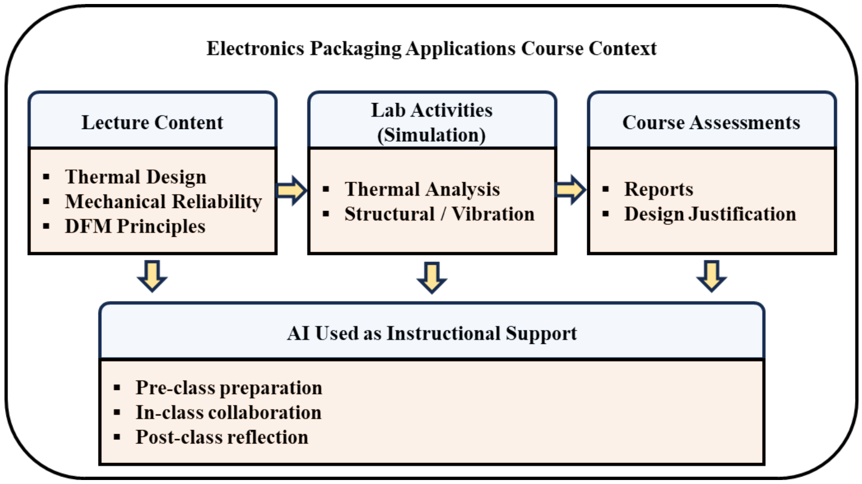

Figure 2: Course context and scope of AI integration within the Electronics Packaging Applications course. AI tools were introduced as instructional supports across preparation, collaboration, and reflection activities, while core course content, structure, and assessment remained unchanged.

3.1.4 Instructional Consistency and Longitudinal Implementation

Implementing the framework across three consecutive semesters enabled iterative refinement informed by instructor observation, student feedback, and performance trends. Throughout this period, core course content, learning objectives, and assessment structures remained unchanged. In contrast, instructional strategies related to AI-assisted pre-class preparation, in-class collaborative discussion, and post-class reflective reporting were progressively refined to improve clarity, usability, and alignment with intended learning outcomes.

This longitudinal implementation provided a stable instructional context for examining how increasingly structured AI integration influenced student learning and perceptions over time. Maintaining consistency in curricular scope and evaluation criteria also enabled meaningful comparison of quantitative performance measures and qualitative feedback across cohorts, strengthening the credibility of observed trends discussed in subsequent sections.

This consistent instructional environment provided a reliable foundation for implementing and evaluating the AI-powered collaborative simulation learning framework presented in Section 4.

3.2. Instructional Intervention

3.2.1 AI-Powered Collaborative Simulation Learning Framework Overview and Design Rationale

The AI-powered collaborative simulation learning framework was designed to address three interrelated challenges identified in prior sections: fragmented learning across analytical domains, limited emphasis on manufacturability reasoning, and unstructured use of AI in engineering education. Rather than introducing AI as a standalone technology intervention, the framework embeds AI support within an enhanced flipped classroom structure that emphasizes preparation, collaboration, and reflective application. To clarify the structure and sequencing of the proposed instructional approach, Figure 3 presents an overview of the AI-powered collaborative simulation learning framework. Table 4 summarizes the learning activities and respective roles of AI and students across the three phases of the framework.

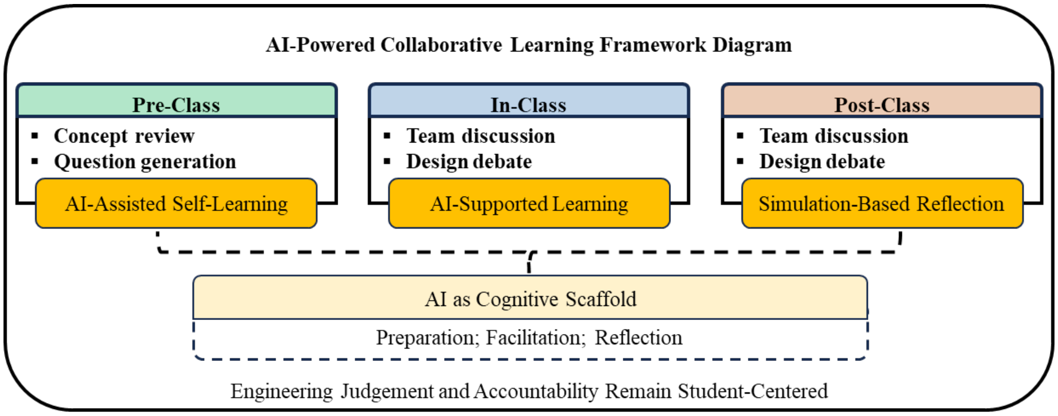

Figure 3: Overview of the AI-powered collaborative simulation learning framework. The framework integrates AI-assisted self-learning before class, AI-supported collaborative design during class, and simulation-based individual reflection after class. AI functions as a cognitive scaffold across all phases, while engineering judgment and accountability remain student-centered.

Table 4: Framework phases, learning activities, and roles of AI and students

Phase	Learning Activities	Role of AI	Student Responsibility
Pre-Class	Concept review, question formulation	Clarification, prompting	Preparation
In-Class	Team discussion, design evaluation	Facilitation, synthesis	Collaborative reasoning
Post-Class	Simulation, reporting, reflection	Feedback, organization	Individual accountability

The framework consists of three sequential and interdependent phases: (1) AI-assisted self-learning before class, (2) AI-supported collaborative design and discussion during class, and (3) simulation-based individual reflection after class. This structure mirrors authentic engineering workflows, in which individual preparation, team-based problem solving, and independent validation coexist. To further clarify the role of AI within the proposed framework, Figure 4 illustrates the boundary between AI cognitive support and student-centered engineering judgment.

3.2.2 Phase I: AI-Assisted Self-Learning (Pre-Class)

In the pre-class phase, students engage in self-directed preparation activities designed to build conceptual readiness for in-class application. AI tools are used to support content review, question generation, and conceptual clarification related to upcoming topics such as thermal management, vibration reliability, or design-for-manufacturability considerations.

Students are provided with guiding prompts that encourage them to interrogate AI-generated explanations, identify assumptions, and connect theoretical principles to potential design implications. Rather than receiving solutions, students are asked to critique and refine AI-assisted responses, fostering self-regulated learning and early exposure to reflective reasoning. This approach helps ensure that students enter the classroom prepared to engage in higher-order discussion and collaborative problem solving.

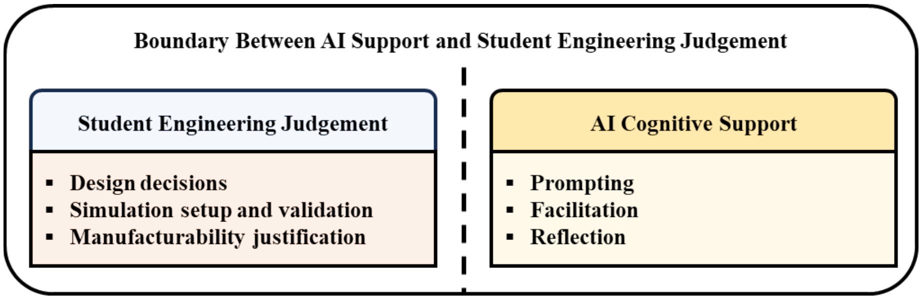

Figure 4: Conceptual boundary between student engineering judgment and AI cognitive support within the proposed framework. AI assists with prompting, synthesis, and reflection, while design decisions, simulation execution, and justification remain the responsibility of students.

3.2.3 Phase II: AI-Supported Collaborative Design (In-Class)

During class sessions, students work in small teams to address open-ended, context-rich design problems drawn from electronic packaging and manufacturing scenarios. These problems require students to balance competing considerations, such as thermal performance, mechanical reliability, material selection, and manufacturability constraints.

AI support in this phase is intentionally limited to facilitation roles. AI tools assist by summarizing discussion threads, highlighting potential trade-offs, and prompting teams to consider alternative design perspectives. Importantly, AI does not generate final design recommendations. Students remain responsible for evaluating suggestions, justifying decisions, and negotiating trade-offs through engineering reasoning and peer discussion.

This structured collaborative environment encourages interdisciplinary communication and shared accountability while reducing dominance effects within teams. By positioning AI as a neutral mediator rather than an expert authority, the framework reinforces the central role of human judgment in engineering design.

3.2.4 Phase III: Simulation-Based Reflection and Individual Extension (Post-Class)

Following in-class collaboration, students individually extend their design work through detailed simulation and analysis activities. Using established simulation workflows, students conduct thermal, structural, and vibration analyses and evaluate the manufacturability implications of their design choices.

In this phase, AI tools support reflective documentation rather than analysis itself. Students use AI-assisted writing and visualization tools to organize simulation results, articulate design rationale, and reflect on discrepancies between predicted performance and manufacturability constraints. Students are required to explicitly justify all conclusions using simulation data and engineering principles, ensuring that AI-assisted support does not replace analytical reasoning.

This individual reflection phase reinforces accountability and deepens learning by requiring students to integrate collaborative insights with independent validation. It also supports the development of professional technical communication skills aligned with industry expectations.

3.2.5 Alignment with Learning Objectives and Assessment

Across all three phases, the framework maintains alignment with existing course learning objectives and assessment criteria. AI-assisted activities are not graded independently; instead, student performance is evaluated based on simulation accuracy, quality of manufacturability reasoning, and clarity of technical communication. By embedding AI within established instructional and assessment structures, the framework avoids dependency on specific technologies and remains adaptable to different institutional contexts. This design choice supports scalability and transferability while preserving academic integrity and instructional consistency.

Table 5 illustrates how the framework components align with targeted learning skills relevant to simulation-based manufacturing education.

Table 5: Alignment between framework components and targeted learning skills

Framework Component	Targeted Skills	Learning Focus
AI-Assisted Preparation	Conceptual understanding	Readiness
Collaborative Design	Teamwork, trade-off analysis	Reasoning
Simulation Reflection	Analysis, communication	Accountability

3.2.6 Representative AI-Supported Learning Interactions

To provide concrete illustration of how artificial intelligence tools were used within the instructional framework, representative examples of student–AI interactions are presented below(Table 6). These examples are not exhaustive but reflect typical usage patterns observed across cohorts. AI tools were employed as scaffolding mechanisms to prompt reasoning, comparison, and reflection rather than to generate final design solutions.

Table 6: Representative AI-supported learning interactions

Instructional Phase	Purpose of AI Use	Representative Student Prompt	Pedagogical Function
Pre-Class Preparation	Concept clarification and question generation	Explain how boundary condition selection influences heat dissipation in PCB simulations and identify assumptions affecting manufacturability.	Supports conceptual grounding and prepares students for simulation setup by encouraging critical evaluation of modeling assumptions.
In-Class Collaboration	Structuring design trade-off discussion	List manufacturability trade-offs when selecting aluminum versus composite materials for heat sink fabrication.	Facilitates comparison of alternatives and promotes multidisciplinary reasoning during team design deliberation.
Post-Class Reflection	Organization of engineering justification	Help outline a justification comparing two simulation configurations in terms of reliability, manufacturability, and cost implications.	Encourages reflective synthesis of results and strengthens technical communication and reasoning articulation.

To provide additional contextual clarity regarding implementation logistics, collaborative AI-supported activities were conducted in small groups of two to three students. In-class engagement with AI-assisted prompts typically occupied approximately 15–20 minutes per session as part of broader collaborative design discussions. While students were encouraged to continue using AI tools outside scheduled class time, such usage was not formally monitored due to its asynchronous and self-directed nature. Structured AI engagement occurred in nearly every class meeting following introduction of the framework, ensuring consistent exposure across instructional phases.

3.3 Assessment Instruments

3.3.1 Assessment Design and Alignment

This study employed a mixed-methods assessment design to examine learning outcomes associated with the AI-powered collaborative simulation learning framework. Assessment strategies were explicitly aligned with the research questions and course learning objectives, focusing on students' ability to (1) conduct accurate and meaningful simulations, (2) reason about manufacturability and reliability constraints, and (3) communicate technical results effectively.

Data were collected across three consecutive semesters to enable longitudinal comparison while maintaining consistency in course content, instructional objectives, and grading criteria. AI-assisted activities were not assessed directly; instead, evaluation focused on student-generated simulation artifacts, written design rationales, and reflective technical reports to ensure that measured outcomes represented student learning rather than AI output.

3.3.2 Quantitative Assessment Instruments

Student performance was evaluated using three quantitative assessment instruments designed to capture complementary aspects of learning aligned with the course objectives and research questions. All instruments were implemented using analytic rubrics with standardized performance descriptors and were applied consistently across all three semesters.

Simulation accuracy and modeling quality were assessed based on students' ability to correctly configure and interpret thermal, structural, and vibration simulations. Evaluation criteria emphasized the appropriateness of boundary conditions, material property selection, mesh quality, solver configuration, and the physical plausibility of simulation results, with particular attention to students' interpretation and justification of outcomes rather than numerical convergence alone.

Manufacturability reasoning was assessed through written design justifications accompanying simulation submissions. This instrument evaluated students' ability to integrate thermal, mechanical, and production considerations, identify and justify trade-offs among competing design criteria, and propose feasible solutions grounded in manufacturing and reliability constraints.

Technical communication quality was evaluated through final reports, focusing on clarity of organization, effective visualization of simulation results, coherence between analysis and conclusions, and adherence to professional engineering communication standards.

To summarize the scope and criteria of these quantitative instruments, Table 7 presents an overview of the assessment dimensions, primary evaluation focus, representative criteria, and scoring ranges.

Table 7:Quantitative assessment instruments and evaluation criteria

Assessment Dimension	Primary Evaluation Focus	Representative Criteria	Score Range
Simulation Accuracy and Modeling Quality	Correct setup and interpretation of engineering simulations	Boundary conditions, material properties, mesh quality, solver configuration, result interpretation	0–100
Manufacturability Reasoning	Integration of design, analysis, and production constraints	Trade-off analysis, feasibility, reliability considerations, justification quality	0–100
Technical Communication	Association with professional engineering reporting	Organization, clarity, visualization, alignment between data and conclusions	0–100

3.4 Data Collection

Qualitative data were collected through post-course surveys and open-ended reflection prompts administered at the end of each semester. Students were asked to reflect on their learning experiences, the role of AI in their design process, and how collaborative and simulation-based activities influenced their reasoning.

Responses were analyzed using thematic analysis. An initial round of open coding was used to identify recurring concepts, followed by axial coding to group responses into higher-level themes. Coding focused on patterns that appeared consistently across cohorts rather than isolated statements.

3.5 Statistical Analysis

To examine performance trends across semesters, a one-way analysis of variance (ANOVA) was conducted for each assessment metric. Assumptions of normality and homogeneity of variance were screened prior to analysis and were not violated; therefore, alternative nonparametric procedures were not required and are not reported. Effect sizes (η^2) were calculated to estimate the magnitude of observed differences across cohorts, and statistical significance was evaluated at an α level of 0.05.

Consistent with classroom-based educational research contexts and nonrandomized cohort structures, results are interpreted as indicators of learning trends rather than causal effects. Accordingly, effect sizes and distributional patterns (Figure 6) are emphasized alongside statistical significance to support interpretation of longitudinal instructional impact.

To clarify how student work artifacts were transformed into analyzable quantitative data, Figure 5 summarizes the assessment and analysis workflow used in this study.

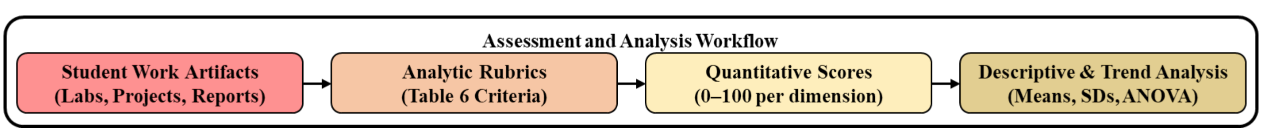

Figure 5: Overview of the assessment and analysis workflow used in this study. Student-generated artifacts were evaluated using analytic rubrics aligned with simulation accuracy,

manufacturability reasoning, and technical communication. Resulting scores were analyzed descriptively and used to identify performance trends across semesters.

3.6 Trustworthiness & Ethics

3.6.1 Reliability, Validity, and Trustworthiness

Several strategies were employed to enhance the reliability and validity of the assessment process. Quantitative rubrics were refined prior to data collection and applied consistently across semesters. Using multiple cohorts strengthened internal consistency, while triangulation between quantitative and qualitative data enhanced construct validity.

For qualitative analysis, themes were derived from repeated patterns across responses rather than individual anecdotes, supporting trustworthiness of interpretation. While the study is limited to a single course context, the consistency of observed trends across semesters strengthens the credibility of the findings.

To summarize the dominant themes identified through qualitative analysis, Table 8 presents the emergent themes and their associated descriptions.

Table 8: Emergent themes from qualitative analysis

Theme	Description
Conceptual Integration	Improved ability to connect simulation results with design decisions
Design Confidence	Increased confidence in evaluating trade-offs and justifying solutions
AI as Cognitive Scaffold	AI perceived as a facilitator rather than an answer generator
Reflective Reasoning	Greater emphasis on explanation, validation, and justification

3.6.2 Ethical and Academic Integrity Considerations

Students were explicitly instructed that AI-generated content could not be submitted as final work without independent verification and justification. Assessment emphasized reasoning processes, simulation configuration, and reflective explanation, reducing the likelihood that AI use could obscure learning deficiencies. This approach aligns with ethical and academic integrity considerations associated with AI use in engineering education.

4. Results

4.1 Overview of Results and Alignment with Research Questions

Building on the assessment framework described in Section 5, this section presents quantitative performance trends and qualitative perceptions across three semesters. Results are reported in direct alignment with the study's research questions. RQ1 examines how AI-enhanced flipped learning supports students' simulation proficiency, manufacturability reasoning, and reflective design communication, while RQ2 focuses on the cognitive and pedagogical benefits associated with embedding AI tools within collaborative design and simulation workflows.

Consistent with the longitudinal and nonrandomized study design, the results emphasize performance trends and distributional patterns across semesters rather than causal effects. Quantitative findings are first presented to address RQ1, followed by qualitative evidence that contextualizes these trends in relation to RQ2.

4.2 Longitudinal Trends in Quantitative Performance (RQ1).

To examine cohort differences across semesters, one-way analyses of variance (ANOVA) were conducted for each assessment metric. Figure 6 and Table 9 provide complementary descriptive and visual references for the performance trends discussed below. Because manufacturability reasoning represents the central cognitive outcome examined in RQ1, distributional visualization is provided specifically for this metric (Figure 6). Simulation accuracy and technical communication outcomes are summarized in Table 9, as their score distributions exhibited comparatively stable patterns across cohorts and were not the primary analytical focus of this investigation.

Across all three assessment dimensions, mean scores demonstrated a consistent upward trend from Fall 2024 to Fall 2025. Improvements were most pronounced in manufacturability reasoning, followed by simulation accuracy, while gains in technical communication were comparatively moderate. In addition to higher mean scores, later cohorts exhibited reduced score variability, indicating more consistent application of simulation-based reasoning and design justification across students.

Importantly, although technical communication maintained the highest absolute performance levels across semesters, followed by simulation accuracy, proportional gains were greater in manufacturability reasoning. This distinction reflects the instructional objective of strengthening students' ability to synthesize simulation outcomes into manufacturing-aware design decisions — a cognitively demanding competency that historically develops more slowly than procedural or reporting skills. Accordingly, longitudinal gains in manufacturability reasoning are interpreted as evidence of alignment between instructional design and the primary research aim.

Figure 6 illustrates the distribution of manufacturability reasoning scores by semester. In particular, the Fall 2025 score distribution shows a higher concentration of scores in the upper performance range and fewer low-performing outliers relative to earlier semesters. This pattern suggests that performance gains were distributed across the cohort rather than driven by a small subset of high-achieving students, directly addressing RQ1's emphasis on strengthening manufacturability reasoning broadly.

Descriptive statistics and inferential results are summarized in Table 9. One-way ANOVA indicated statistically significant cohort effects for manufacturability reasoning and simulation accuracy, accompanied by medium effect sizes, suggesting meaningful variation across instructional implementations. Differences in technical communication were smaller and did not consistently reach statistical significance. Consistent with classroom-based educational research contexts and nonrandomized cohort structures, these findings are interpreted as indicators of longitudinal instructional trends rather than causal effects attributable to a single intervention.

Table 9: Descriptive statistics, 95% confidence intervals of cohort means, and one-way ANOVA results comparing student performance across semesters.

Metric	Fall 2024 M (SD)	Spring 2025 M (SD)	Fall 2025 M (SD)	95% CI of Mean Range	F(2,62)	p	η^2
Simulation Accuracy	89.65 (4.8)	91.61 (4.3)	92.48 (3.9)	[88.1, 93.9]	4.72	.012	.13
Manufacturability Reasoning	80.2 (7.4)	82.4 (7.4)	87.6 (5.8)	[78.0, 89.8]	7.91	.001	.20
Technical Communication	87.73 (5.1)	88.15 (4.9)	89.28 (4.4)	[86.3, 90.7]	1.83	.168	.06

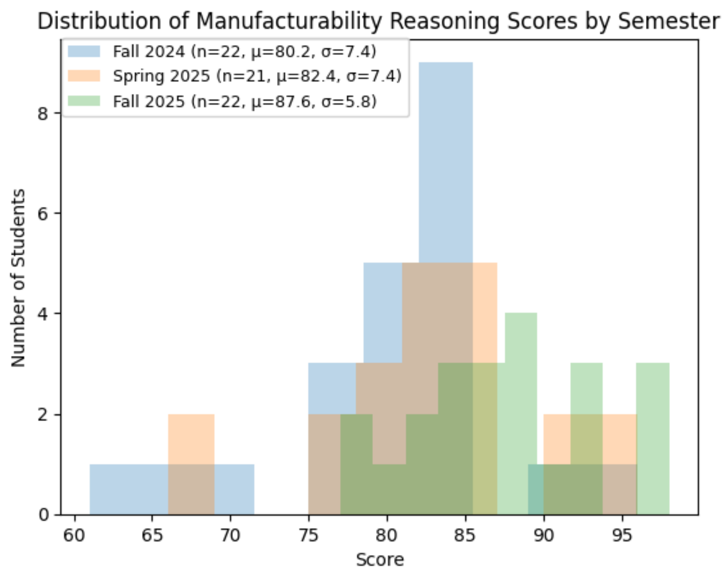

Figure 6: Distribution of manufacturability reasoning scores by semester. Histograms illustrate score distributions across three semesters. Legend entries report sample size (n), mean score (μ), and standard deviation (σ) for each cohort.

4.3 Interpretation Relative to Instructional Context (RQ1 and RQ2)

Although causal claims are not made, the progression of score distributions aligns with the staged integration of AI-supported instructional practices across semesters. Fall 2024 relied primarily on traditional simulation-centered instruction. In Spring 2025, AI tools were introduced as optional supports for laboratory and project work. By Fall 2025, AI-assisted self-learning and AI-supported collaboration were systematically embedded within a flipped classroom structure.

This progression provides contextual grounding for interpreting quantitative patterns discussed in Section 4.2. From the perspective of RQ1, strengthened cohort-wide performance in manufacturability reasoning aligns with instructional structures designed to promote integrative justification of design decisions. From the perspective of RQ2, these patterns suggest that AI tools, when positioned as instructional supports rather than solution generators, may contribute to more equitable participation in design reasoning and more coherent articulation of manufacturability considerations.

4.4 Qualitative Evidence of Cognitive and Pedagogical Benefits (RQ2)

Qualitative analysis of post-course surveys and reflective responses provides complementary evidence addressing RQ2. Students frequently described AI tools as supporting idea organization, comparison of alternative solutions, and validation of reasoning pathways. Rather than relying on AI-generated answers, students emphasized using AI to prompt reflection, structure explanations, and check assumptions during both collaborative discussions and individual reporting.

These perceptions align with the quantitative trends observed in Figure 6, particularly the reduction in low-performing scores and increased consistency across cohorts. Collectively, the qualitative findings suggest that AI-supported collaboration and reflection may help lower barriers for students who previously struggled to articulate manufacturability reasoning, while preserving the central role of human engineering judgment.

4.5 Synthesis of Findings Relative to RQ1 and RQ2

Taken together, quantitative and qualitative findings provide convergent evidence addressing both research questions. In direct response to RQ1, longitudinal score patterns indicate improved justification of design decisions within manufacturing and reliability constraints. These gains were distributed across cohorts rather than concentrated among high-performing individuals, suggesting broad engagement with manufacturability reasoning.

In response to RQ2, qualitative data suggest that these improvements are associated with cognitive and pedagogical benefits arising from AI's role as an instructional scaffold within collaborative and reflective workflows. When considered alongside quantitative trends, these findings suggest that structured AI integration may support both the development and articulation of manufacturability reasoning without displacing human-centered engineering judgment.

The results characterize AI-supported flipped simulation instruction as a context associated with enhanced integrative reasoning and reflective design practice, establishing the foundation for the pedagogical implications discussed in Section 5.

5. Discussion and Implications

5.1 Interpretation of Findings in Relation to Research Questions

The results presented in Section 6 provide convergent quantitative and qualitative evidence addressing both research questions. With respect to RQ1, the observed upward shifts and increased concentration in manufacturability reasoning scores suggest that students became more capable of articulating design decisions grounded in manufacturing and reliability constraints. Importantly, these improvements were distributed across cohorts rather than confined to a small group of high-performing students, indicating broader engagement with manufacturability-aware reasoning.

In relation to RQ2, qualitative findings indicate that students experienced AI tools as cognitive and organizational supports that facilitated reflection, comparison of alternatives, and justification of decisions. Rather than displacing engineering judgment, AI-supported workflows appeared to help students externalize and structure their reasoning processes, aligning with the framework's human-centered intent.

5.2 Pedagogical Implications for Engineering Education

The findings suggest that the educational value of AI in engineering contexts lies less in automating technical tasks and more in supporting reasoning, reflection, and collaboration. When embedded intentionally within a flipped, simulation-intensive course, AI tools can function as instructional scaffolds that help students connect analytical results to manufacturability considerations and communicate design rationale more coherently.

From a pedagogical perspective, the staged implementation observed in this study highlights the importance of integrating AI gradually and purposefully. The progression from optional AI support to systematic AI-assisted preparation and collaboration aligns with improved consistency in student performance, suggesting that structured integration may be particularly beneficial for supporting students who struggle with open-ended design justification.

5.3 Implications for Manufacturability-Focused Curriculum Design

Electronic packaging education requires students to reason across thermal, mechanical, and production domains simultaneously. The results of this study suggest that AI-supported collaborative simulation environments may help address long-standing challenges in teaching manufacturability by providing prompts, organizational structure, and comparative perspectives that are difficult to achieve through traditional instruction alone.

By emphasizing justification, trade-off analysis, and reflection rather than numerical convergence, the proposed framework aligns simulation-based learning more closely with authentic engineering practice. This approach may be transferable to other manufacturing-oriented courses where students must balance competing constraints and articulate design decisions beyond tool operation.

Beyond the immediate instructional context, the findings also point toward broader implications for emerging AI literacy frameworks and Industry 5.0 workforce preparation. As engineering practice increasingly requires practitioners to critically evaluate AI-generated information, interpret computational outputs, and integrate multidisciplinary constraints into decision-making, educational environments must cultivate not only technical proficiency but also reflective human–AI collaboration skills. The framework explored in this study contributes to this direction by positioning AI as a structured support within authentic engineering workflows rather than as a task automation mechanism. Such approaches may support the development of AI-aware engineering judgment aligned with evolving expectations for adaptive, human-centered engineering practice.

5.4 Limitations and Directions for Future Work

Several limitations should be considered when interpreting these findings. The study was conducted within a single course context with modest cohort sizes and nonrandomized semester groups, limiting the generalizability of results. Additionally, while longitudinal trends are evident, causal relationships between specific instructional elements and learning outcomes cannot be established.

Future work will focus on developing more fine-grained instruments to assess AI literacy and manufacturability reasoning, as well as exploring predictive models for automated feedback on design feasibility. Expanding the framework to additional courses and institutions would further support validation and refinement of the proposed approach.

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