Toward a Verification and Validation Framework for Strategic AI Integration in Engineering Education: Instructor Reflections Across Three Use Cases

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Toward a Verification and Validation Framework for Strategic AI Integration in Engineering Education: Instructor Reflections Across Three Use Cases

Abstract

The integration of generative artificial intelligence (AI) tools in engineering education presents both opportunities and challenges for educators seeking to preserve academic standards while enhancing learning outcomes. This study addresses the research question: How can verification and validation principles be applied as a structured pedagogical framework to support the strategic integration of AI into engineering courses, improving learning while maintaining academic rigor? Using a qualitative use-case approach based on instructor reflections from three use cases spanning graduate and undergraduate engineering courses, we document pedagogical innovations that transform AI from an academic integrity concern into an explicit learning tool that scaffolds student development within the Zone of Proximal Development. Drawing on these verification and validation principles, along with the Definition, Abstraction, and Implementation framework, we examine AI integration from both instructor-centered (top-down) and student-centered (bottom-up) perspectives. The latter is represented through instructor observation of student work and engagement rather than direct student-reported data. Our findings suggest that strategic AI integration, when grounded in structured pedagogical frameworks and applied across both perspectives, shows promise for enhancing learning experiences and instructor teaching practices without compromising academic standards. These findings point toward directions for future empirical validation.

1 Introduction

The rapid advancement of AI tools presents both challenges and opportunities for engineering education. While many educators express concerns about AI's potentially negative impacts on academic integrity and learning outcomes, research suggests that the effective integration of AI tools in engineering coursework can benefit both instructors and students. This paper examines the strategic integration of AI tools in engineering education from both instructor-centered and student-centered perspectives, with the goal of identifying frameworks that preserve academic rigor while enhancing learning. This study addresses the research question: How can verification and validation principles be applied as a structured pedagogical framework to support the strategic integration of AI into engineering courses, improving learning while maintaining academic rigor?

2 Background

2.1 AI Integration in Engineering Education: Current Landscape

The integration of AI tools in higher education has generated significant debate among educators. While some institutions have moved to restrict AI use due to academic integrity concerns, others recognize AI's potential to enhance learning when strategically implemented [1, 2]. Engineering education faces particular challenges as computing and data-intensive tools become central to engineering work, yet educators remain responsible for cultivating students' fundamental analytical and problem-solving capabilities [3, 4, 5, 6].

Recent AI-augmented systems engineering work shows how large language models and graph-based representations can support dynamic data integration and reasoning in complex system-of-systems contexts [7]. Such advances demonstrate AI's growing capabilities in engineering domains, yet work translating these technical capabilities into effective pedagogical strategies remains limited.

Recent studies on AI in engineering education have identified both opportunities and challenges [3, 8]. More broadly, the integration of digital tools into engineering coursework has been shown to present similar implementation challenges, particularly when adoption is rapid or externally driven [9]. Students report increased productivity and access to resources, while instructors express concerns about skill development and over-reliance [10]. However, most existing frameworks either prohibit or permit AI use, with limited guidance on strategic integration that maintains academic rigor while leveraging AI's benefits.

2.2 Verification and Validation in Engineering Practice

Verification and validation (V&V) is a fundamental principle in systems engineering [11]. Verification ensures that a system is built correctly according to specifications, while validation confirms that the right system was built to meet user needs [12]. In systems engineering practice, V&V provides systematic methods for evaluating complex systems against requirements [13]. These principles extend naturally to educational contexts, where students must verify their understanding against established principles and validate their solutions against real-world requirements. Adapted to the engineering education context, these V&V principles can be applied through a three-step process (Figure 1) applicable to both instructor and student perspectives.

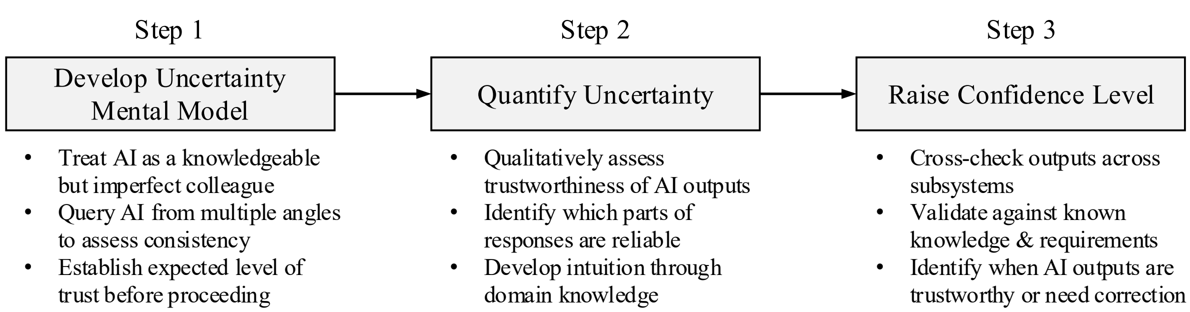

Figure 1: Three-Step Verification and Validation (V&V) Process for AI Use in Engineering Education

First, instructors and students develop an uncertainty mental model, learning to treat AI outputs similarly to advice from a knowledgeable but imperfect colleague. Just as engineers verify information by consulting multiple experts, both instructors and students can query AI from multiple angles or roles to assess consistency and raise the confidence level in the responses [14]. Second, instructors and students engage in uncertainty quantification, developing the ability to assess the trustworthiness of AI-generated content, both qualitatively and quantitatively, by identifying which parts of a response are reliable and which require further verification [15]. Third, instructors and students learn strategies to raise the confidence level in AI outputs, particularly when dealing with complex, multi-part problems in which subsystem uncertainties must be propagated into a coherent answer [13].

2.3 DAI Framework for AI-Integrated Engineering Education

Prior work by Tsutsui and DeLaurentis [16] discussed the Definition, Abstraction, and Implementation (DAI) framework (Figure 2) for aerospace structural mechanics education. This established framework provides a structured methodology that serves both educators (instructors) and learners (students) in approaching complex engineering problems.

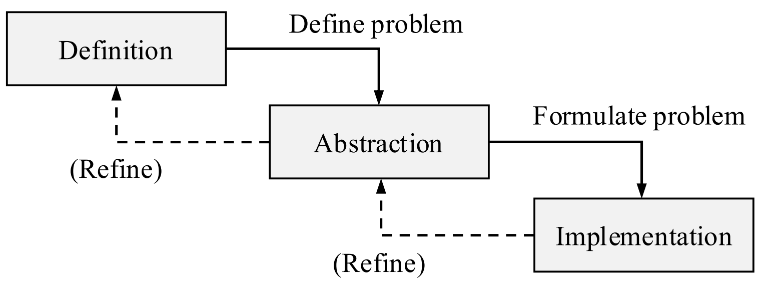

Figure 2: Definition, Abstraction, and Implementation (DAI) Process [16]

- **Definition**: Clearly articulating the problem and identifying what needs to be solved.
- **Abstraction**: Simplifying the problem by identifying key principles and relationships.
- **Implementation**: Applying solutions and validating results.

While DAI has shown promise in traditional engineering education contexts, its application to AI-integrated learning environments remains unexplored. Extending this framework to address the unique challenges of AI integration could provide the pedagogical structure currently missing from engineering education approaches.

2.4 Educational Perspectives in Engineering Pedagogy

Engineering education literature recognizes the importance of both instructor-centered (top-down) and student-centered (bottom-up) perspectives in curriculum design [14, 17]. As illustrated in Figure 3, the top-down approach examines how instructors structure courses and design curricula, while the bottom-up approach examines how students navigate learning and develop skills. Effective pedagogical frameworks should address both perspectives to ensure comprehensive educational impact.

However, these perspectives have not been systematically applied to AI integration in engineering courses. Furthermore, the integration of these dual perspectives with established engineering principles like V&V and structured frameworks like DAI remains unexplored in the context of AI-assisted learning.

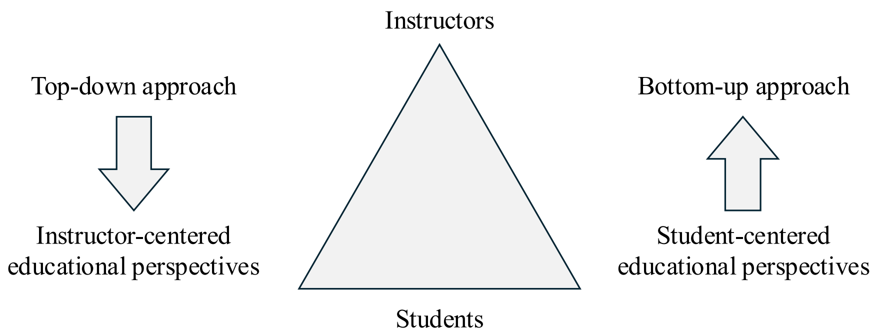

Figure 3: Educational Perspectives: Instructor-Centered vs. Student-Centered Approaches

2.5 Gap in Strategic AI Integration

Current approaches to AI in engineering education tend toward extremes: either prohibiting AI use entirely or allowing unrestricted access without pedagogical structure. This represents a significant gap: while V&V principles are fundamental to engineering practice and DAI provides a structured problem-solving approach, these established frameworks have not yet been systematically applied to AI integration from both instructor-centered and student-centered perspectives. Current discussions rarely connect AI integration to V&V principles or systematic pedagogical frameworks, thereby missing opportunities to develop students' critical evaluation skills essential for both effective AI use and professional practice. Critical thinking and information literacy have been recognized as foundational engineering competencies, with efforts to develop validated instruments to assess these skills in engineering contexts [18], yet their connection to AI integration remains underexplored. Rigorous assessment frameworks that connect learning objectives to broader competencies are equally essential to this integration [19].

This study addresses this gap by integrating V&V and DAI principles through complementary top-down and bottom-up approaches, creating a comprehensive framework for strategic AI integration. The framework is applied through structured assignments that require instructors and students to verify and validate AI-generated outputs against established knowledge and independent analyses, thereby promoting critical evaluation skills while maintaining academic rigor.

3 Methodology

This research examines AI integration in engineering education through a qualitative use case approach based on instructor reflections and pedagogical experiences. This methodology documents and analyzes pedagogical innovations and implementation strategies. The analysis focuses on assignment design, student engagement patterns, and observed learning outcomes when AI tools are strategically incorporated into coursework.

3.1 Instructor-Reflection Approach

The research team conducted structured reflective discussions with instructor-authors who have experimented with AI integration in their engineering courses. These discussions took the form of collaborative self-reflection sessions in which each instructor documented their pedagogical rationale, implementation experiences, and observed student engagement patterns. While these sessions involved dialogue among the research team, they are grounded in instructor reflection rather than formal interview protocols with external participants. These discussions explored the pedagogical rationale behind AI-inclusive assignments, implementation challenges encountered, observed patterns in student work and engagement, and lessons learned from these implementations.

This instructor-centered approach, consistent with prior work demonstrating the value of structured instructor-led interventions in aerospace engineering courses [20, 21], provides valuable insights into practical strategies for AI integration while acknowledging the limitations of not having systematic student data collection. Because all three use cases are examined through instructor reflection, student-centered (bottom-up) perspectives are represented as instructor observations of student activity and engagement rather than as direct student-reported data.

3.2 Use Case 1 (Top-Down Approach): AI as an Instructor Tool in Multiple Electrical and Computer Engineering (ECE) Graduate and Undergraduate Courses

Course Context: This use case draws on multiple ECE courses spanning both graduate and undergraduate levels. Across these courses, assessments are administered as closed-book, in-person, pen-and-paper multiple-choice exams with no calculators permitted. Questions are deliberately designed with simple numbers to avoid the need for computational tools and are decoupled from one another to prevent errors in one question from cascading into subsequent ones.

Assignment Design: The instructor used AI as a verification tool for exam design rather than as a student-facing assignment. Specifically, the instructor uploaded exam questions to an AI system to evaluate question quality, checking for example whether questions were appropriately decoupled, whether the numerical values were reasonable, and whether the overall exam effectively tested conceptual understanding. The instructor also explored AI's ability to answer the exam itself, observing that AI could achieve approximately 90% accuracy on ECE material. This estimate is based on instructor observation during exam review, not systematic benchmarking.

Pedagogical Rationale: This use case represents a top-down, instructor-centered application of AI. Rather than integrating AI into student assignments, the instructor leveraged AI as a design-review aid, analogous to using a knowledgeable colleague to sanity-check assessment materials. This approach preserves full instructor ownership of exam design and upholds academic integrity, while using AI to identify potential weaknesses in question construction and verify that questions are well-posed and appropriate for the undergraduate level.

The key principle here is that AI serves as a quality assurance tool that supports instructor judgment, not a replacement for it. Notably, the in-person, no-calculator exam format represents a deliberate structural safeguard that renders AI inaccessible during assessment, sidestepping AI-related academic integrity concerns entirely.

Pedagogical Approach: This use case is characterized as a top-down approach because the primary actor is the instructor, who uses AI to design, verify, and validate assessment materials. The flow of decision-making moves from the instructor downward, with AI serving as a tool that supports instructor judgment rather than engaging students directly.

3.3 Use Case 2 (Bottom-Up Approach): AI as an Exploratory Tool in a Graduate Decision-Based Engineering Design Course

Course Context: ME 541 (Engineering Design: A Decision-Based Perspective) is a graduate-level course that introduces students to systematic decision-making frameworks for engineering design problems. The course emphasizes multi-criteria decision-making under uncertainty, utility theory, and recognition of heuristics and biases in design decisions. Students learn to formulate engineering design decisions, apply multi-attribute utility theory, and adopt an interdisciplinary approach to engineering design and systems engineering. The course covers topics ranging from probability theory and utility theory to behavioral decision-making and group decision processes.

Assignment Design: As a voluntary assignment (extra credit opportunity), students were invited to submit a short report exploring how AI technologies could improve decision-making in the design process, enhance learning in the course, or both. Students were encouraged to propose creative and innovative ideas supported by relevant examples, and to demonstrate those ideas where possible. The voluntary assignment was evaluated on creativity, use of examples, demonstration, and critical thinking.

Pedagogical Rationale: This voluntary report serves multiple educational purposes within the decision-based design context. By inviting students to propose and demonstrate their own ideas for AI integration, the assignment encourages meta-level reflection on the course material and asks students to think critically about where AI can and cannot support sound engineering decision-making. This student-driven, bottom-up approach gives students the freedom to draw on course concepts, such as utility theory, bias recognition, and multi-criteria decision-making, and apply them as evaluative lenses to assess AI's capabilities and limitations.

Rather than prescribing a specific AI interaction, the open-ended format rewards creativity and critical thinking, encouraging students to move beyond passive consumption of AI outputs toward more active and informed engagement with the technology. This student-driven reflection aligns with collective-learning approaches in engineering design education, where students construct a shared understanding through active engagement with course concepts [22]. The voluntary nature of the assignment also provides a low-stakes environment in which students can experiment with AI tools and develop their own perspective on how these tools align with or fall short of the rigorous decision frameworks taught in the course. Together, these elements position the assignment as a bottom-up complement to the instructor-centered course structure, inviting students to take ownership of their engagement with AI rather than following a prescribed AI interaction.

Pedagogical Approach: This use case is characterized as a bottom-up approach because the primary actors are the students, who independently explore and evaluate AI's role in engineering design based on their own understanding of course concepts. Rather than following a prescribed AI interaction defined by the instructor, students drive the process themselves, generating insights that flow upward and inform broader discussions about AI integration in engineering education. As with all use cases in this study, however, this bottom-up activity is documented through instructor observation rather than direct student data collection.

3.4 Use Case 3 (Hybrid Top-Down/Bottom-Up Approach): AI as a Comparative Lens in a Graduate System-of-Systems Engineering Course

Course Context: AAE 560 (System-of-Systems Engineering) is a graduate-level course that introduces students to methodologies for analyzing complex, interconnected systems. The course emphasizes critical evaluation of different modeling approaches and their applicability to various system-of-systems characteristics. Students in this course are expected to engage with primary literature and develop independent analytical capabilities.

Assignment Design: Students conducted a literature review on methodologies from the Solberg Chart, shown in Figure 4. Students were required to: (1) independently identify which of Maier's system-of-systems traits their chosen methodology best addresses, (2) prompt ChatGPT to perform the same analysis, and (3) submit both their own analysis and ChatGPT's response, along with the prompt they used.

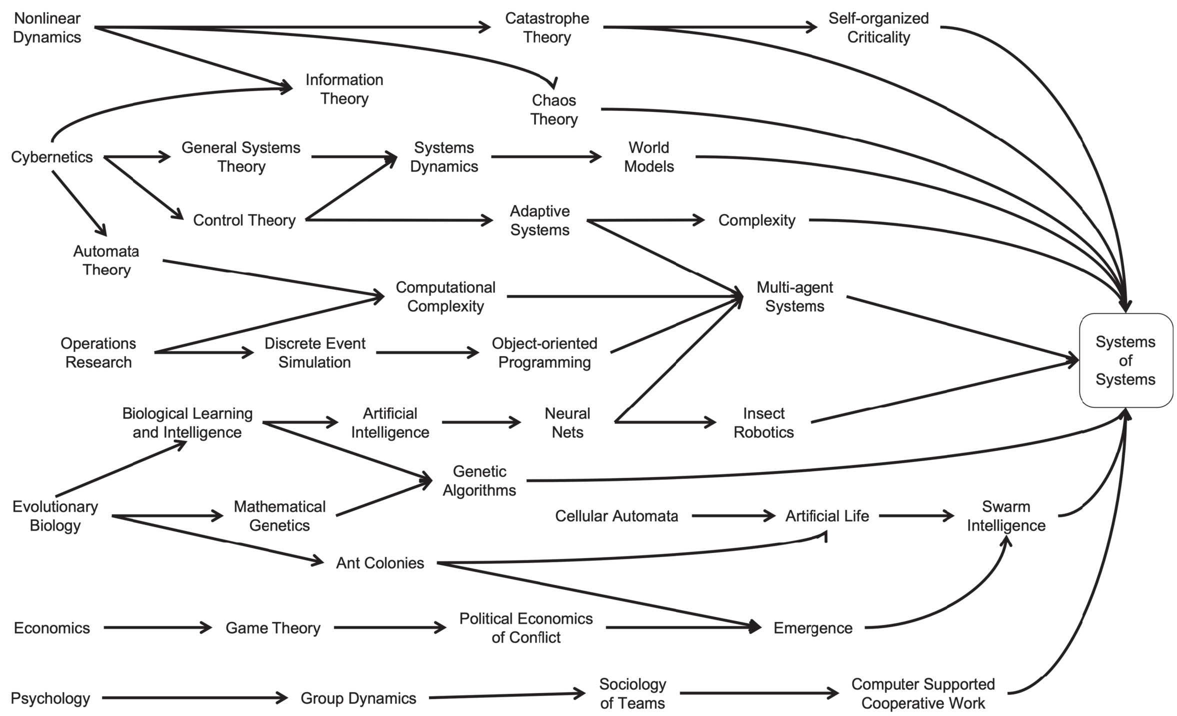

Figure 4: The Solberg Chart showing the lineage of systems modeling methodologies relevant for system-of-systems analysis [23]

To give context to this assignment, Maier's system-of-systems characteristics include operational independence, managerial independence, geographic distribution, evolutionary development, and emergent behavior. When a system exhibits all five of these characteristics, it is appropriately regarded as a system of systems rather than a monolithic system [24]. For example, the Internet is widely regarded as a system of systems because it satisfies each of Maier's characteristic patterns [23, 25].

Pedagogical Rationale: This assignment was designed to help students learn about system-of-systems methodologies while also critically evaluating AI-generated content, effectively transforming AI from a potential integrity concern into an explicit pedagogical tool. According to the instructor, this design serves multiple educational purposes. It requires students to develop their own understanding before consulting AI, ensuring foundational knowledge development. By having students compare their reasoning with ChatGPT's output, they engage in critical evaluation of AI-generated content. The dual-submission requirement creates transparency that discourages academic misconduct while promoting honest engagement with AI tools.

Pedagogical Approach: This use case is characterized as a hybrid top-down and bottom-up approach, combining elements of both perspectives. From the top down, the instructor deliberately structures the assignment to require independent analysis before AI consultation, establishing clear expectations and transparency requirements through the dual-submission format. From the bottom up, students actively engage with AI tools, critically evaluate AI-generated outputs against their own reasoning, and develop independent analytical capabilities. Together, these complementary perspectives provide a balanced framework that integrates instructor-guided structure and student-driven inquiry.

3.5 Analytical Framework: Verification and Validation

Figure 5 illustrates how this study applies the V&V framework analytically. Each use case is examined against the three DAI stages (Definition, Abstraction, and Implementation) to assess how AI integration was applied and evaluated across different course contexts. All use cases in this study demonstrate V&V principles in practice, with each of the three V&V steps (developing an uncertainty mental model, quantifying the uncertainty, and raising the confidence level) corresponding to a distinct stage of the DAI process.

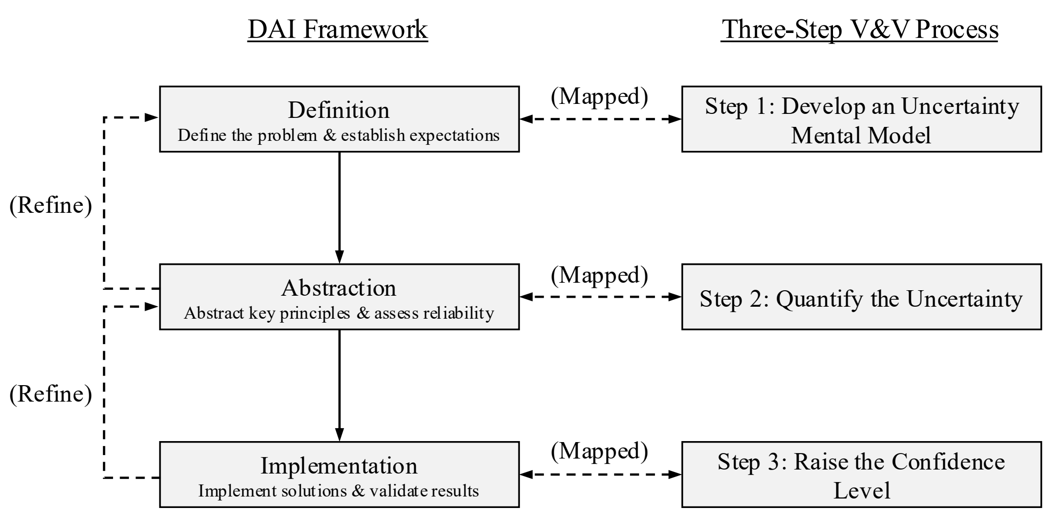

Figure 5: Mapping of the Three-Step V&V Process onto the Definition, Abstraction, and Implementation (DAI) Framework

The mapping between the DAI stages and the three-step V&V process is grounded in conceptual alignment rather than mere structural convenience. At the Definition stage, both frameworks require the practitioner to establish expectations and bound the problem space, which corresponds to developing an uncertainty mental model by determining what level of trust is appropriate before engaging with AI outputs. At the Abstraction stage, both frameworks call for identifying which principles and relationships are reliable, which corresponds to uncertainty quantification, where the practitioner assesses the trustworthiness of AI-generated content using domain knowledge as an evaluative lens. At the Implementation stage, both frameworks require validating results against established knowledge, mirroring the process of raising the confidence level by cross-checking outputs and verifying them against known requirements. This conceptual alignment suggests that V&V and DAI are compatible and complementary frameworks when applied to AI integration in engineering education [14, 26].

In Use Case 1, the instructor applies V&V principles from the top down: at the definition stage, the instructor articulates the learning objectives the exam must assess; at the abstraction stage, AI is used to verify that questions are well-posed and appropriately scoped; and at the implementation stage, the instructor validates that the overall assessment measures student understanding of the intended material.

In Use Case 2, students apply V&V thinking through a bottom-up, student-driven process. At the definition stage, students identify and articulate how AI could improve decision-making or enhance learning in the course. At the abstraction stage, they draw on course concepts such as utility theory, bias recognition, and multi-criteria decision-making as evaluative lenses to assess AI's capabilities and limitations. During implementation, students validate their proposed ideas through concrete examples and demonstrations, critically reflecting on where AI aligns with or falls short of the rigorous decision frameworks taught in the course.

In Use Case 3, the dual-submission requirement structures student engagement with the full DAI cycle. Students must first define their analytical approach and identify which SoS traits apply to their chosen methodology, then abstract key characteristics from the literature to form their own judgment, and finally verify their analysis against AI-generated outputs during implementation, while validating both responses against established SoS literature.

This cross-case consistency demonstrates that the combined V&V and DAI framework provides a robust and transferable structure for AI integration across diverse engineering education contexts, from instructor-centered assessment design to student-centered critical analysis. Taken together, the three use cases illustrate how the same underlying framework can manifest differently depending on the course level, subject matter, and whether the primary perspective is top-down or bottom-up.

4 Results and Discussion

4.1 Findings from Use Case Analysis

4.1.1 Use Case 1: ECE Graduate and Undergraduate Courses

The ECE courses implementation demonstrated that AI can serve as a top-down quality-assurance tool in assessment design. The instructor reported uploading both midterm and final exam questions to an AI system to evaluate question quality before administering the exams. A key finding was that AI could achieve approximately 90% accuracy on ECE material. This performance level lends credibility to AI as a reviewer capable of identifying poorly constructed or ambiguous questions prior to assessment.

A central pedagogical observation from this use case concerns the deliberate decoupling of exam questions. This decoupling design proved effective, and the instructor found AI useful for identifying hidden dependencies that could introduce cascading errors, serving as a systematic check that complements the instructor's own judgment. This mirrors the V&V principle of verification, where the exam is checked to ensure it is built correctly before being administered.

The in-person, closed-book, no-calculator format of the exams serves as a structural safeguard that effectively mitigates AI-related academic integrity concerns during assessment. Rather than monitoring AI use, the exam format makes it a non-issue by design. The instructor also noted a broader opportunity for AI to support student learning beyond formal assessments, observing that students could use AI to independently generate practice problems on specific topics, along with correct solutions. For this bottom-up use of AI to be effective, however, students would still need to apply V&V principles, verifying the accuracy of AI-generated problems and solutions against their own understanding and course material. This bottom-up use of AI for self-directed practice was identified as a promising complement to the instructor-centered application discussed in this section, suggesting that top-down and bottom-up approaches can coexist within the same course context.

Beyond exam verification, the instructor identified a promising opportunity to deepen AI integration into learning management systems. Specifically, the instructor envisioned using AI to generate quiz questions with unique numerical values for each student. Because each student receives questions with different numerical values, direct copying of answers becomes ineffective, encouraging independent thinking and promoting academic integrity.

4.1.2 Use Case 2: Decision-Based Engineering Design Course

The ME 541 implementation demonstrated that open-ended, reflective assignments can reveal a broad and nuanced understanding of AI's capabilities and limitations in engineering decision-making, reflecting the depth of engagement that student-driven, low-stakes assignments can produce. As with all use cases in this study, the following observations are drawn from instructor review of student submissions rather than direct student-reported data. Students drew meaningfully on course concepts such as utility theory, bias recognition, and multi-criteria decision-making as evaluative lenses for assessing AI's role in engineering design. Some submissions demonstrated the ability to identify where AI tools fall short of the rigorous decision frameworks taught in the course, recognizing that AI may overlook important attributes or introduce cognitive biases in ways that violate sound decision theory principles. These observations echo findings that decision quality depends critically on how problems are framed and how domain knowledge is applied [15].

Figures 6 through 10 present a structured taxonomy derived from student submissions to the optional assignment. Figure 6 provides a high-level overview of the themes students identified, organized into four categories: AI in Design Process, AI in Learning Enhancement, Challenges and Limitations, and Specific AI Methodologies. Figures 7 through 10 expand each category in turn, reflecting the range and depth of student-generated ideas.

Figure 7 captures student proposals for AI in the design process, including generative design, data analysis, bias mitigation, and aerodynamic optimization. Figure 8 summarizes learning enhancement ideas such as conversational AI tutors, gamification strategies, personalized education platforms, and administrative support tools. Figure 9 maps student-identified challenges and limitations across technical and data concerns, human factors, and economic and ethical dimensions. Figure 10 identifies specific AI methodologies students proposed for engineering design contexts, including Bayesian Networks, Monte Carlo Simulations, Reinforcement Learning, and Natural Language Processing.

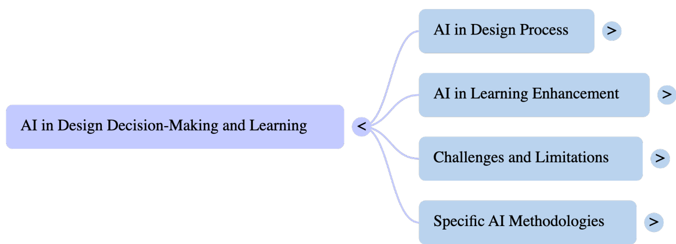

Figure 6: Overview of AI applications in design decision-making and learning

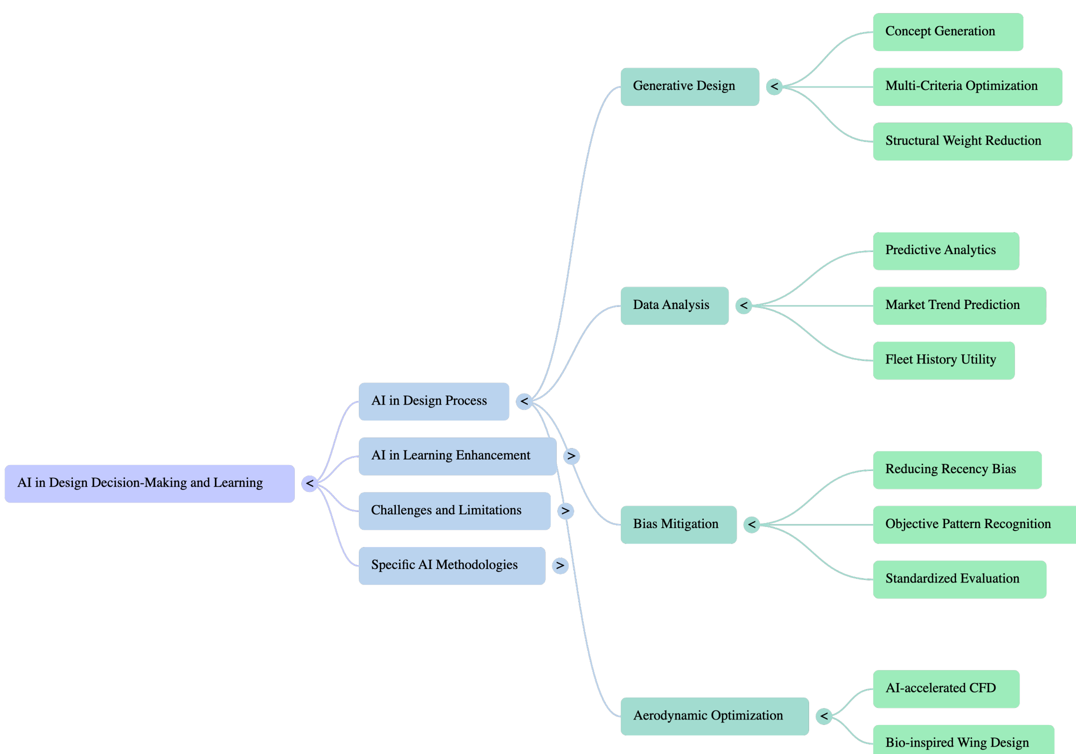

Figure 7: AI in Design Process: key application areas

Student submissions varied considerably in depth. Many responses provided straightforward descriptions of AI tools and their potential applications, whereas others engaged more critically with the course material. The stronger submissions stood out by using course concepts as evaluative lenses rather than simply listing AI capabilities. For example, some students drew on multi-attribute

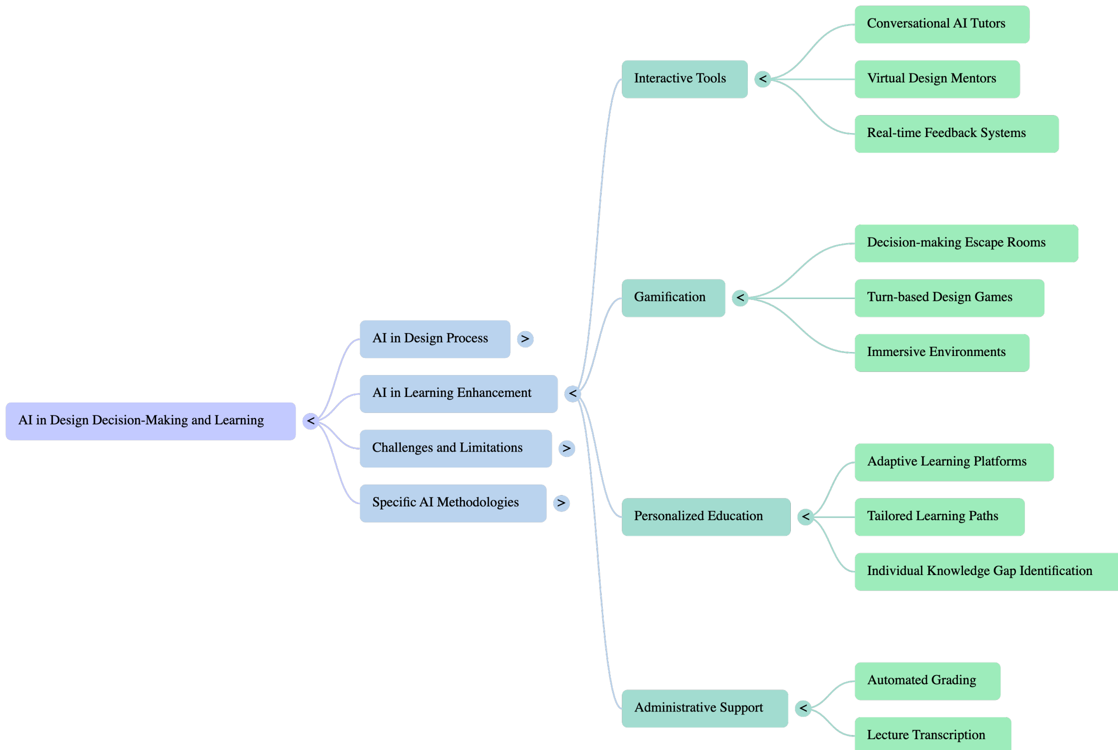

Figure 8: AI in Learning Enhancement: tools and strategies

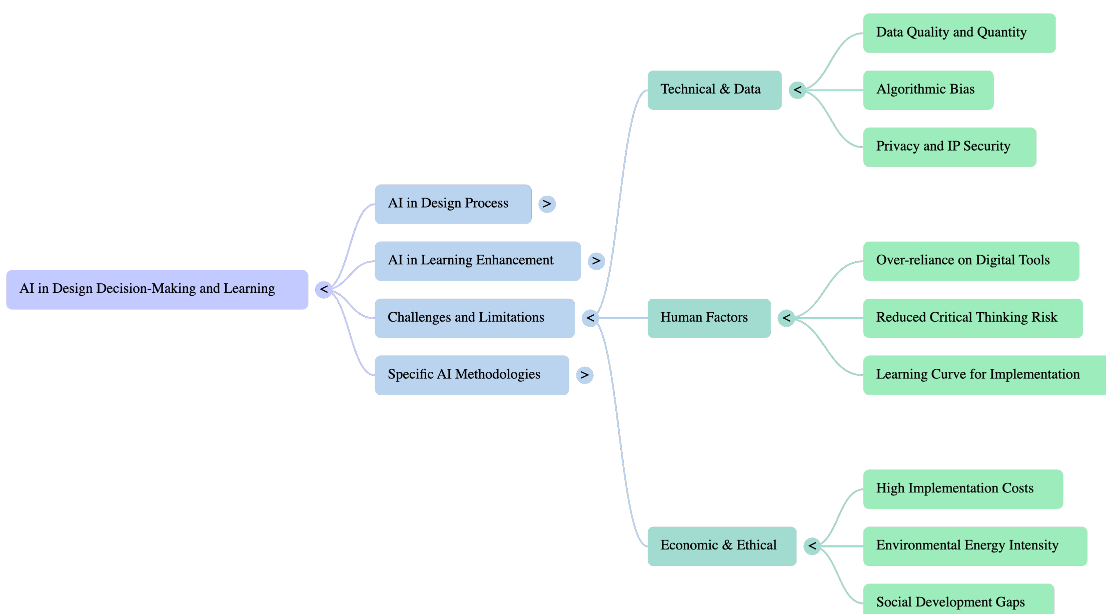

Figure 9: Challenges and Limitations of AI integration

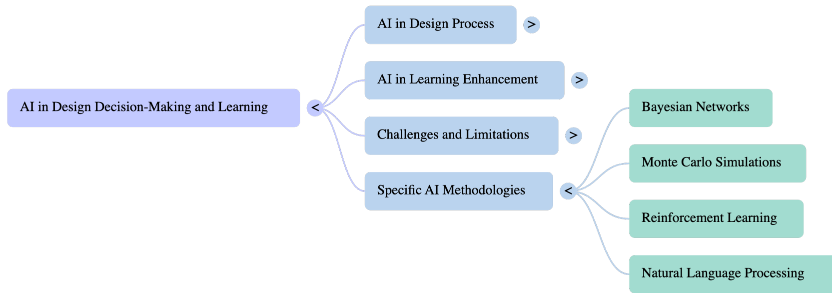

Figure 10: Specific AI methodologies for engineering design

utility theory to argue that AI design recommendations carry hidden assumptions about how attributes should be weighted, assumptions that properly belong to the engineer and not the tool. Weaker submissions, by contrast, tended to catalog what AI can do without asking whether those capabilities align with sound decision-making principles.

This variation is itself a meaningful finding. The open-ended format created space for genuine critical reflection among students who engaged deeply. At the same time, the uneven depth across submissions suggests that future iterations of this assignment could benefit from more explicit scaffolding, for instance, by prompting students to evaluate AI tools specifically against the decision frameworks taught in the course rather than leaving that connection implicit.

4.1.3 Use Case 3: System-of-Systems Engineering Course

The AAE 560 implementation revealed several important patterns regarding student engagement with AI tools. The instructor reported that the dual-submission format effectively revealed cases in which students relied too heavily on AI rather than engaging in independent thought. These instances were readily apparent when students' analyses closely matched ChatGPT's response without evidence of critical engagement or original reasoning. Importantly, the transparency required by the dual-submission format did not merely expose over-reliance; it provided the instructor with an opportunity to address it directly, reinforcing the expectation that students must develop and defend their own analytical reasoning before consulting AI.

An unexpected pedagogical benefit emerged from the assignment: the instructor observed that ChatGPT frequently provides inconsistent responses, generating different lists of Maier's traits across similar queries. For example, when multiple students queried ChatGPT about the same methodology, they received varying characterizations of which SoS traits applied. This inconsistency was initially surprising but proved to be pedagogically valuable.

Rather than undermining the assignment, this variability became a powerful teachable moment, demonstrating to students the importance of V&V of AI outputs, a core principle in systems engineering. Students who encountered these inconsistencies were prompted to return to the primary literature to resolve discrepancies, reinforcing the habit of grounding their analyses in established sources rather than accepting AI-generated content uncritically. This outcome aligns directly with the V&V framework's emphasis on raising confidence through cross-checking and independent validation.

4.2 Challenges in AI Integration

While the preceding use cases suggest that AI tools can serve as valuable educational resources, successful implementation faces significant obstacles. These challenges span technical and pedagogical concerns, institutional and cultural barriers, and deeper questions about academic integrity. Together, they make clear that strategic AI integration requires more than thoughtful assignment design alone.

Technical and Pedagogical Challenges: Several implementation challenges emerged at the course design level. A recurring need across all three use cases was clear guidelines on the appropriate use of AI that distinguish between acceptable assistance and academic misconduct [27]. The instructors faced the complex task of redesigning assignments to complement rather than compete with AI capabilities, requiring a fundamental rethinking of assessment methods. Additionally, concerns have emerged that students may become over-reliant on AI tools, which can reduce the quality of their mental effort, undermine problem-solving abilities, and impair the development of independent critical thinking skills [28].

Institutional and Cultural Challenges: Beyond course-level challenges, the instructors observed systemic barriers to AI integration. These include inconsistent institutional policies across departments, lack of faculty training, faculty reluctance to adopt a new instructional paradigm, and student confusion arising from varying expectations across courses [29]. Time constraints for instructors to develop AI-literate curriculum and the rapid pace of AI tool evolution further complicate the implementation efforts. A persistent challenge across all three use cases was establishing appropriate boundaries between AI-assisted work and independent work, requiring ongoing dialogue between instructors and students.

Underlying Academic Integrity Challenges: This study takes the position that AI amplifies pre-existing academic integrity challenges rather than creating fundamentally new ones, a perspective consistent with Perkins [30]. Just as students exhibit varied preferences for independent versus collaborative work, they now must navigate similar choices regarding AI assistance. This finding suggests that AI integration requires addressing longstanding questions about learning ownership and academic honesty that go beyond any specific tool or technology.

4.3 Opportunities from AI Integration

Despite these significant challenges, our implementation across all use cases revealed compelling benefits that emerge from thoughtful AI integration. When instructors address the challenges proactively through structured frameworks like V&V, AI tools can meaningfully enhance both student learning outcomes and instructional practices. These opportunities span both student learning outcomes (bottom-up opportunities) and instructor pedagogical practices (top-down opportunities).

Student Learning Enhancement: Among the bottom-up improvements, AI tools enhanced student productivity by automating routine tasks, freeing students for conceptual understanding and design iterations, an effect empirically confirmed in professional task settings by Noy and Zhang [31], though the finding may not transfer directly to engineering coursework. The technology enabled personalized learning pathways, with AI providing feedback and scaffolding for diverse learning needs, consistent with prior work showing that technology-enhanced visualization tools can meaningfully improve students' understanding of complex engineering concepts [32]. Additionally, students developed valuable AI literacy skills that will be essential in their future engineering careers, a need increasingly recognized at the institutional level, as evidenced by Purdue University's recent adoption of an AI working competency graduation requirement [33, 34].

Instructor Teaching Enhancement: Across the use cases, AI integration created opportunities to transform pedagogical approaches. These top-down enhancements enabled the instructors to focus classroom time on developing higher-order thinking skills, including system-level design thinking and creative problem-solving, rather than transmitting procedural knowledge. AI tools enable more sophisticated project assignments that mirror real-world engineering practice, in which AI assistance is increasingly standard. This approach suggests that instructors can also leverage AI to rapidly prototype teaching materials and provide personalized student feedback tailored to each student's current level of understanding.

AI as an Adaptive Scaffold for Student Learning: Drawing on Vygotsky's concept of the Zone of Proximal Development (ZPD) [35], which was originally conceived in the context of human-mediated scaffolding by a more knowledgeable peer or teacher, AI tools can be understood as occupying an analogous, if distinct, scaffolding role, consistent with prior applications of the ZPD framework in engineering education contexts [36]. As illustrated in Figure 11, the ZPD represents the space in which AI scaffolding operates, bridging what students can do alone (i.e., the innermost region, labeled the Zone of Independence, representing what students can accomplish without AI assistance) and what currently lies beyond their reach (i.e., the outermost region, labeled the Zone Beyond Current Reach, representing what students cannot yet do even with AI).

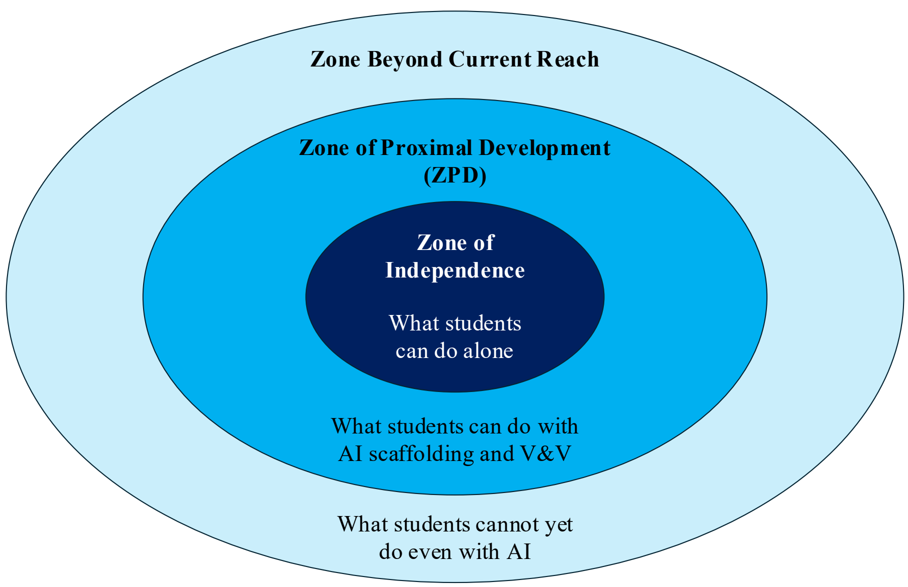

Figure 11: ZPD applied to AI scaffolding and V&V in engineering education

Within the ZPD, the V&V framework provides the structure for students to critically evaluate AI outputs rather than passively accepting them, ensuring that AI serves as a genuine learning tool rather than a shortcut. Specifically, by developing an uncertainty mental model, quantifying the reliability of AI responses, and actively raising the confidence level, students engage with AI in a way that deepens rather than bypasses their own understanding.

This analogy, however, has important limitations that are worth acknowledging. As a knowledgeable conversation partner, AI can provide targeted support that advances students' understanding without replacing the cognitive work students must do themselves. Yet AI lacks the intentionality and social awareness central to Vygotsky's original conception. In other words, unlike a human teacher or peer who consciously adapts their support to the student's social and emotional context, AI provides scaffolding (i.e., structured help) without genuine awareness or intent, which represents a meaningful departure from the framework as originally formulated.

4.4 Verification and Validation as Pedagogical Strategy

This section examines how V&V principles can be applied as a deliberate pedagogical strategy, addressing both the opportunities and risks that arise when AI tools are integrated into engineering coursework.

Shifting from Answer Generation to Critical Evaluation: To balance AI's learning benefits against concerns about over-reliance, the integration of AI necessitates a pedagogical shift away from focusing solely on generating correct answers toward teaching students to verify and validate AI-generated outputs. Doing so demands careful attention to what constitutes valid evidence of learning in an AI-integrated environment [19]. This shift also trains students to think like systems engineers, using AI as a supporting tool rather than a substitute for their own creative thinking and ingenuity. Students should learn to use AI strategically, drawing on their existing domain knowledge to validate AI-generated answers, organize ideas, and conduct reasoned searches. By establishing checkpoints throughout their work, students maintain ownership of their learning and develop the ability to validate each step of the AI's reasoning, rather than treating AI as a shortcut that does the work for them.

Treating AI as an Imperfect Colleague: A useful mental model for students is to treat AI as they would a highly capable but imperfect engineering colleague. Just as one would not blindly accept advice from even a senior engineer without some degree of verification, students should develop the habit of cross-checking AI outputs. They can do this by asking the same question from different angles or prompting AI to take on different roles. Consistent answers across these varied prompts can reasonably increase confidence in the output, whereas inconsistencies signal the need for more rigorous verification. This mirrors how experienced engineers build trust in complex systems by evaluating the reliability of each component before drawing conclusions from the system's output. This approach also involves designing verification scenarios at each stage of problem-solving, particularly for topics where existing knowledge can serve as a benchmark, thereby addressing the boundary-setting challenges identified in the Institutional and Cultural Challenges section while leveraging AI's capacity to support higher-order engineering thinking.

Reinforcing the Three-Step V&V Process: This pedagogical shift also reinforces the three-step V&V process introduced earlier. Students who develop a sound uncertainty mental model, practice uncertainty quantification, and actively seek to raise the confidence level in AI outputs are better positioned to use AI as a genuine learning tool rather than a shortcut. These habits of mind are not only valuable in academic settings but are increasingly essential in professional engineering practice, where AI tools are becoming standard components of the design and analysis workflow.

4.5 Synthesis: Responding to the Research Question

Taken together, the findings across all three use cases offer a direct response to this study's guiding research question: How can verification and validation principles be applied as a structured pedagogical framework to support the strategic integration of AI into engineering courses, improving learning while maintaining academic rigor? Table 1 summarizes the three use cases across key dimensions.

Table 1: Cross-case comparison of three use cases

Dimension	Use Case 1 ECE courses	Use Case 2 ME 541	Use Case 3 AAE 560
Course level	Graduate and undergraduate	Graduate	Graduate
Assessment type	Exam	Report	Literature review
Primary actor	Instructors	Students	Both instructors and students
Approach	Top-down	Bottom-up	Hybrid top-down/bottom-up
Integrity mechanism	Closed-book, in-person format	Voluntary, open-ended format	Mandatory, dual-submission format
Key finding	AI-assisted quality assurance	AI-capability reflection	AI-output evaluation

The evidence suggests three enabling conditions. First, AI integration benefits from explicit pedagogical framing that positions AI as a tool to support rather than replace human judgment, whether that of the instructor or the student. Second, the V&V framework provides a transferable structure that works across course levels and disciplines, from undergraduate exam design to graduate systems analysis. Third, the complementary use of top-down, bottom-up, and hybrid perspectives ensures that AI integration serves both instructor goals and student learning needs simultaneously, as demonstrated across the three use cases.

This was most evident in Use Case 3. The dual-submission format simultaneously served the instructor's transparency goals and the students' need to develop independent analytical reasoning. Academic rigor was maintained not by restricting AI access but by designing assignments and assessment formats that required independent reasoning alongside AI engagement. These conditions together constitute a practical model for strategic AI integration that other engineering educators can adapt to their own contexts.

4.6 Limitations

This study's findings are based on structured reflective discussions with instructors from three use cases. In the interest of transparency, the research team acknowledges that, as instructors reflecting on their own course implementations, their assessments of student engagement and learning may reflect their familiarity with and personal investment in the approaches described. While this approach provided depth of insight into implementation strategies and pedagogical rationale, it relied on insider reflection rather than on externally validated data collection. That is, the instructor-reflection methodology captured pedagogical insights but did not include systematic assessment of student outcomes.

Future research with formal data collection and controlled comparisons could validate and extend these findings. Despite these limitations, the use cases provide concrete examples of AI integration strategies that other instructors can adapt to their contexts, and the V&V framework offers a transferable approach grounded in established systems engineering principles.

5 Conclusions and Future Work

Conclusions: In response to the question of how verification and validation principles can be applied as a structured pedagogical framework to support the strategic integration of AI into engineering courses, this study established a practical framework centered on V&V that maintains academic rigor while promoting authentic learning experiences. Across the three use cases, distinct contributions emerged. In the ECE courses, the instructors demonstrated how AI can serve as a top-down quality-assurance tool for exam design, verifying question construction and decoupling, while preserving full instructor ownership of assessment. In ME 541, the open-ended voluntary assignment showed how student-driven, bottom-up engagement with AI can reveal nuanced critical thinking about AI's capabilities and limitations in engineering decision-making. In AAE 560, the dual-submission format illustrated how a hybrid approach can transform AI from an academic integrity concern into an explicit pedagogical tool, with AI's inconsistency itself becoming a teachable moment about the importance of V&V.

Together, these use cases suggest that thoughtfully implemented AI tools can serve as valuable educational resources while addressing concerns about academic integrity and learning outcomes. The research identified transferable best practices, including assignment designs that require independent reasoning alongside AI engagement, AI-assisted learning activities that promote critical thinking, V&V approaches that train students to think like systems engineers, and assessment methods that evaluate conceptual understanding. These findings offer engineering educators across disciplines practical guidance for curriculum redesign, suggesting that strategic AI integration, when grounded in structured pedagogical frameworks, can meaningfully enhance both teaching and learning.

Future Work: Future research should expand this work in several directions. First, a systematic assessment of student learning outcomes comparing AI-integrated and traditional sections would provide quantitative validation of the V&V approach. Second, longitudinal studies that track students across multiple courses could examine how AI literacy and critical evaluation skills develop over time. Third, expansion to additional undergraduate courses and multiple institutions would test the framework's generalizability. Fourth, the development of assessment rubrics specifically designed to evaluate students' V&V of AI outputs would provide practical tools for educators implementing this approach.

Finally, the integration of AI into learning management systems represents a compelling direction for future development. AI-powered question generation embedded directly in learning management systems, such as Brightspace, could enable instructors to automatically generate numerically distinct questions for each student, thereby enhancing both the quality of AI-assisted assessment design and each student's opportunity for independent learning.

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