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Redefining Experiential Learning and Curriculum Design in the Age of Artificial Intelligence

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Abstract

Experiential learning, spanning project-based courses, laboratory experiences, undergraduate research, internships for academic credit, and industry-sponsored design, has long served as a primary mechanism through which engineering students develop professional competencies aligned with accreditation outcomes and workforce expectations [1] – [3]. The integration of generative artificial intelligence (AI) into engineering practice is fundamentally reshaping these environments, challenging traditional assumptions about "hands-on" learning, authorship, and competency assessment. Rather than functioning solely as a productivity tool, AI increasingly acts as a cognitive collaborator that redistributes human effort and transforms how students engage in engineering problem-solving and design [8], [12].

This paper examines how AI reconfigures experiential learning across a coordinated ecosystem of academic and workplace-integrated environments within an undergraduate electrical and computer engineering program. Drawing on multi-source qualitative evidence from project-based courses, laboratory instruction, undergraduate research, internships for academic credit, and capstone design, the study analyzes how AI shifts student effort from execution toward higher-order activities such as engineering judgment, validation, and communication.

Survey responses from 178 undergraduate engineering students indicate widespread adoption of generative AI across experiential learning environments. Quantitative findings are complemented by qualitative analysis of open-ended responses, revealing that while AI accelerates implementation tasks, students increasingly identify validation, interpretation, and engineering judgment as the primary sources of learning.

The paper introduces an AI-Augmented Experiential Learning Ecosystem model that conceptualizes how cognitive responsibility is dynamically distributed between human learners and AI systems across both phases of engineering work and learning contexts. Across learning contexts, the dominant site of learning shifts from the production of solutions to the validation and interpretation of AI-generated outputs. While AI accelerates prototyping and lowers barriers to entry, it simultaneously introduces new forms of epistemic uncertainty that require explicit emphasis on validation, transparency, and accountability. This paper contributes a theoretically grounded and empirically informed framework for aligning experiential learning with the realities of AI-mediated engineering practice.

1. Introduction

Experiential learning occupies a central role in engineering education, providing students with opportunities to integrate theoretical knowledge with authentic problem-solving across a range of instructional and professional contexts [1], [4]. Through project-based courses, laboratory instruction, undergraduate research, and internships for academic credit, students encounter the complexities of real-world engineering work, including ambiguous problem definitions, competing constraints, and the need for effective collaboration and communication [2], [5]. These experiences are widely recognized as essential for developing the technical and professional competencies required for engineering practice.

At the same time, the emergence of generative artificial intelligence (AI) tools is transforming the nature of engineering work itself. Tools such as large language models and AI-assisted development environments now support tasks including code generation, design exploration, data analysis, and technical communication. These tools enable engineers to operate at higher levels of abstraction, shifting effort away from routine implementation tasks and toward more integrative and evaluative forms of work [8], [12]. As a result, students are increasingly incorporating AI into their workflows across both academic and workplace-integrated environments.

This transformation introduces a fundamental tension within experiential learning. Traditional models assume that learning is grounded in direct engagement with execution tasks, where students construct understanding by building, testing, and refining artifacts. However, when execution can be partially delegated to AI, the relationship between activity and learning becomes fundamentally altered. Students may produce functional artifacts without fully understanding the processes that generated them, raising concerns about authorship, assessment validity, and the development of deep expertise [9], [11]. These concerns are particularly acute in experiential learning environments, where assessment has historically relied on tangible outputs as primary evidence of competence.

Rather than diminishing the value of experiential learning, this paper argues that AI fundamentally reconfigures where and how learning occurs. Specifically, it shifts the dominant site of learning, the phase in which the most cognitively demanding and educationally meaningful work occurs, from the production of solutions to the validation and interpretation of AI-generated outputs**.** In this reconfigured process, students learn less from generating initial solutions and more from interrogating those solutions, identifying hidden assumptions, resolving inconsistencies, and making decisions under uncertainty. This shift represents not a reduction in cognitive demand, but a redistribution toward higher-order processes that are central to professional engineering practice.

To examine this transformation, this paper is guided by three research questions. The first asks how the integration of AI tools redistributes cognitive effort across phases of engineering work in experiential learning environments. The second investigates what new forms of failure, uncertainty, and learning emerge as students interact with AI across academic and workplace-integrated contexts. The third considers how experiential learning environments should be designed and assessed to support the development of professional competencies in AI-augmented engineering practice.

In responding to these questions, this paper makes three contributions. First, it introduces an AI-Augmented Experiential Learning Ecosystem model that extends experiential learning theory by explicitly accounting for the dynamic distribution of cognitive responsibility between human learners and AI systems across multiple contexts and phases of work. Second, it provides empirical insight into how students engage with AI across project-based courses, laboratory environments, undergraduate research, internships for academic credit, and capstone design, identifying recurring patterns that reshape both effort allocation and learning outcomes. Third, it proposes a framework for curriculum design and assessment that foregrounds validation, transparency, and engineering judgment as central competencies in AI-mediated environments.

These contributions suggest that experiential learning in the age of AI is no longer defined by direct execution alone, but by the supervision, validation, and integration of machine-augmented work. The paper provides a foundation for aligning engineering education with the evolving realities of professional practice.

2. AI-Augmented Experiential Learning Ecosystem

Experiential learning has traditionally been conceptualized as a cyclical process in which learners engage in concrete experience, reflect on that experience, develop conceptual understanding, and apply that understanding in new situations [1]. Within engineering education, this process has been operationalized through activities such as design projects, laboratory experiments, and internships, where students directly engage in the execution of tasks as a means of constructing knowledge and developing professional competence. These models implicitly assume that learning is tightly coupled with the act of producing artifacts, such that understanding emerges through doing.

The integration of generative artificial intelligence (AI) challenges this foundational assumption by decoupling execution from understanding. When students can partially delegate implementation tasks to AI systems, the relationship between activity and learning becomes less direct. As a result, experiential learning must be reconceptualized not as a bounded process within individual courses, but as a distributed system in which human and machine contributions are interdependent and evolve across contexts.

To capture this shift, this paper introduces the AI-Augmented Experiential Learning Ecosystem, which conceptualizes learning as occurring across a network of interconnected environments, including early-stage project-based courses, laboratory instruction, undergraduate research, internships for academic credit, and capstone design. Each of these contexts contributes uniquely to student development while collectively shaping how students learn to engage with AI in engineering practice. Importantly, these environments are not isolated; rather, they form a progression in which students encounter increasing levels of complexity, autonomy, and accountability.

A defining feature of this ecosystem is the dynamic redistribution of cognitive responsibility between human learners and AI systems across both contexts and phases of engineering work. This redistribution is not uniform but instead follows a recurring pattern that can be understood through three phases of AI-mediated experiential learning: problem framing, solution generation, and validation and integration.

In the *problem framing phase*, human cognition remains dominant. Students are responsible for defining the problem, identifying constraints, interpreting stakeholder needs, and establishing design objectives. These activities require contextual understanding, domain knowledge, and the ability to navigate ambiguity, capabilities that AI systems cannot reliably replicate. As a result, this phase continues to serve as a critical foundation for meaningful engagement in engineering work.

In the *solution generation phase*, AI systems play a more prominent role. Students increasingly rely on AI tools to generate candidate solutions, including code, system architecture, and documentation. This phase is characterized by rapid iteration and exploration, as AI enables students to quickly produce and evaluate multiple alternatives. While this accelerates the development process, it also introduces the risk of superficial understanding, as students may accept AI-generated outputs without fully interrogating their underlying assumptions.

In the *validation and integration phase*, cognitive responsibility shifts decisively back to the human. Students must evaluate AI-generated outputs, test their correctness, identify inconsistencies, and ensure that solutions function as intended within the broader system. This phase requires the application of engineering judgment, including the ability to reason under uncertainty, reconcile conflicting information, and take responsibility for decisions. Across contexts, this phase consistently emerges as the most cognitively demanding and educationally significant, as it is where students engage most deeply with the material.

This three-phase structure highlights a fundamental transformation in the nature of experiential learning. Rather than being centered on the production of solutions, learning increasingly occurs through the validation and interpretation of those solutions. In this sense, the role of the student shifts from that of a primary producer to that of a supervisor and integrator of machine-generated work. This shift does not diminish the importance of experiential learning; instead, it relocates its cognitive center of gravity toward higher-order processes that are more closely aligned with contemporary engineering practice.

Moreover, this redistribution of effort becomes more pronounced as students move across the experiential learning ecosystem. Early-stage courses emphasize exploration and conceptual understanding, where AI serves as a scaffold for learning. In contrast, internships and advanced design experiences require students to operate in environments where errors have real consequences, and where validation and accountability are essential. This progression reflects a shift in competency expectations, from learning how to generate solutions to learning how to evaluate, refine, and take responsibility for them.

The AI-Augmented Experiential Learning Ecosystem provides a framework for understanding how learning evolves in response to AI and for designing educational experiences that align with the realities of modern engineering practice.

3. Methods

This study employs a qualitative, practice-based research approach designed to examine how students engage with generative artificial intelligence (AI) across multiple experiential learning contexts. The methodological approach is grounded in the analysis of authentic instructional environments rather than controlled experimental conditions, reflecting the complex and situated nature of engineering education. In this context, the goal is not to isolate variables, but to understand how patterns of behavior and learning emerge as students interact with AI within realistic academic and workplace-integrated settings.

The study is situated within an undergraduate electrical and computer engineering program at a research-intensive institution and draws on a coordinated set of experiential learning environments, including project-based courses, laboratory instruction, undergraduate research experiences, internships for academic credit, and capstone design. These contexts were intentionally considered together to capture how student engagement with AI evolves across the broader experiential learning ecosystem rather than within a single course.

Across multiple academic terms, an anonymous survey was administered to undergraduate engineering students enrolled in experiential learning environments, including project-based courses, laboratory instruction, undergraduate research, internships for academic credit, and capstone design. A total of 178 valid responses were collected.

Data sources were intentionally multi-modal to support triangulation and increase the robustness of the analysis. Primary sources include project artifacts such as design reports, code repositories, and technical documentation, which provide direct evidence of how students structured their work and integrated AI-generated outputs. These artifacts were supplemented by structured AI-use disclosure statements, in which students were required to explicitly document where and how AI tools were used, the nature of the outputs generated, and the strategies employed to validate those outputs. Additional data were drawn from faculty and teaching assistant observations recorded throughout the project lifecycle, as well as recurring themes identified through interactions with internship supervisors and industry mentors who engaged with students in professional settings.

The AI-use disclosure instrument was designed to capture not only the presence of AI use, but also the context and purpose of that use. To reflect differences across learning environments, the instrument was adapted to align with the structure and expectations of each context. In early-stage project-based and laboratory courses, disclosures emphasized how AI supported learning, exploration, and initial development. In more advanced contexts, including capstone design and internships for academic credit, disclosures focused more heavily on validation, accountability, and decision-making, reflecting the higher stakes associated with system performance and professional responsibility.

The analysis followed a qualitative thematic approach, focusing on identifying recurring patterns in how students interacted with AI and how those interactions shaped learning outcomes. Coding was conducted iteratively, beginning with open coding to identify emergent categories of AI use, followed by focused coding to refine these categories into broader themes aligned with the research questions. Particular attention was given to identifying patterns related to the redistribution of cognitive effort, the emergence of failure modes, and the development of engineering judgment. These themes were then examined across contexts to identify both commonalities and context-specific variations.

Descriptive statistics were used to provide light empirical grounding for the qualitative findings. These include estimates of AI adoption rates, which ranged from approximately seventy to eighty-five percent of teams across contexts, as well as the prevalence of reported issues associated with AI-generated outputs. These quantitative indicators are not intended to establish causal relationships, but rather to support the interpretation of qualitative patterns and to provide a sense of scale.

This methodological approach enables a cross-context analysis of AI-mediated experiential learning that is both grounded in authentic practice and analytically rigorous. The study captures how students engage with AI not only as a tool, but as an integral component of their learning environment by combining artifact analysis, structured disclosures, and observational data. This approach is particularly well-suited to addressing the research questions, which focus on how cognitive effort is redistributed, how new forms of learning emerge, and how educational environments should respond to these changes.

4. Results

The analysis reveals a consistent and consequential redistribution of cognitive effort across experiential learning contexts, reflecting a fundamental shift in how students engage with engineering work in AI-augmented environments. Across all contexts examined, the dominant site of learning, the phase in which students engage in the most cognitively demanding and educationally meaningful work, shifts from the production of solutions to the validation and interpretation of AI-generated outputs. Students reported spending substantially less time generating initial solutions and significantly more time diagnosing, testing, and refining those solutions. This pattern was observed across project-based courses, laboratory environments, undergraduate research, internships for academic credit, and capstone design, indicating a systemic transformation rather than a context-specific effect.

To situate these patterns across different experiential learning environments, Table 1 summarizes how AI use, failure modes, and dominant learning activities vary across contexts.

Table 1. Cross-Context Patterns of AI Use and Learning Activity

Learning Context	AI Use Frequency	Typical Failure Modes	Dominant Learning Activity	Primary Competency Development
Early Project-based courses	Moderate (60-70%)	Misinterpretation of concepts, overgeneralization	Exploration and iteration	Conceptual understanding
Laboratory Courses	High (70-80%)	Configuration errors, syntax, mismatches	Debugging and correction	Technical proficiency
Internship for Credit	Very High (80-90%)	Context mismatch, hidden assumptions	Validation and verification	Professional judgement
Capstone Design	Very High (85-95%)	System integration failures	System-level validation	Decision-making and accountability

As shown in Table 1, while AI use is widespread across all contexts, the dominant learning activity transitions from exploration and solution generation toward validation and accountability as students move into more advanced and workplace-integrated environments. This distribution supports the proposed redistribution of cognitive effort across phases of engineering work.

Importantly, this shift does not reduce the cognitive demands of experiential learning; rather, it redistributes them. Tasks that were traditionally procedural, such as writing initial code or assembling baseline system components, are increasingly supported or accelerated by AI tools. In contrast, tasks that require interpretation, judgment, and integration become more central to the learning process. Students are required to evaluate the correctness of AI-generated outputs, identify inconsistencies, reconcile competing assumptions, and ensure that system-level behavior aligns with design intent. As a result, learning becomes concentrated in activities that require higher-order cognitive engagement.

Three recurring patterns illustrate how this redistribution manifests in practice. The first involves AI-generated solutions that are locally correct but globally inconsistent. Students frequently encountered outputs that appeared functional in isolation but failed when integrated into larger systems due to mismatched assumptions or incomplete configurations. For example, in embedded systems projects, AI-generated code often correctly implemented individual functions but conflicted with hardware-specific requirements or system-level timing constraints. Resolving these issues required students to move beyond surface-level correctness and engage in deeper reasoning about system interactions.

The second pattern involves loss of traceability, in which students relied on AI-generated outputs without maintaining a clear understanding of how those outputs were produced. In these cases, students were able to generate working components quickly but struggled to diagnose failures when they occurred, as they lacked insight into the underlying logic of the generated solutions. This lack of transparency limited their ability to justify design decisions and increased the time required to resolve issues. In contrast, teams that maintained explicit records of AI use, including prompts, modifications, and validation steps, demonstrated greater control over their designs and were more effective in resolving errors.

The third pattern reflects the emergence of validation as the dominant learning activity. Across contexts, students spent a substantial portion of their effort testing AI-generated outputs, identifying discrepancies, and iteratively refining their designs. This process often involved cross-referencing outputs with technical documentation, conducting targeted experiments, and revising assumptions based on observed behavior. In many cases, students reported that the most significant learning occurred during this phase, as it required them to engage deeply with both the system and the limitations of the AI tools they were using.

These patterns are further reinforced when comparing behavior across learning contexts. In early-stage project-based and laboratory courses, AI use was often oriented toward exploration and rapid prototyping, with students using AI to generate initial solutions and test ideas. While validation was still present, it was less systematic and often driven by immediate functional needs. In contrast, in internships for academic credit and capstone design projects, validation and accountability became central. Students operating in these contexts were more likely to encounter complex system interactions and higher stakes associated with failure, leading to more rigorous testing, documentation, and justification of decisions. This contrast suggests that while AI use is pervasive across contexts, the nature of learning shifts as expectations for performance and accountability increase.

A particularly important finding is the relationship between validation practices and observed performance. Teams that explicitly documented their use of AI and engaged in structured validation practices consistently demonstrated stronger outcomes across contexts. These teams were more effective in diagnosing integration failures, identifying incorrect assumptions, and articulating the rationale behind their design decisions. In contrast, teams with limited transparency in AI use were more likely to experience persistent errors and exhibit gaps in understanding. This pattern suggests that validation and traceability are not only pedagogically significant but also predictive of performance in AI-augmented environments.

These findings indicate that AI does not simplify experiential learning but transforms its structure. The complexity of engineering work remains, but it is redistributed toward activities that require interpretation, validation, and decision-making. This transformation has important implications for how learning is understood, supported, and assessed, as it suggests that the development of expertise is increasingly tied to the ability to critically engage with and take responsibility for machine-generated outputs.

5. Assessment of AI-Augmented Professional Competence

The redistribution of cognitive effort observed in AI-augmented experiential learning environments necessitates a corresponding shift in how student performance is assessed. Traditional assessment models in engineering education have relied heavily on the evaluation of final artifacts, such as code functionality, system performance, and documentation quality, as proxies for student competence. However, when AI systems contribute substantially to the production of those artifacts, the validity of such measures becomes increasingly limited. In these contexts, evaluating what students produce is insufficient without also understanding how those outcomes were generated and how students engaged with AI throughout the process.

The findings presented in this study indicate that learning in AI-mediated environments is increasingly concentrated in the validation and interpretation of machine-generated outputs rather than in their initial production. As a result, assessment must shift from a product-oriented model to a process-oriented model that captures how students interact with AI as part of their problem-solving workflow. This shift reflects a broader redefinition of engineering competence, in which the ability to supervise, evaluate, and take responsibility for automated systems becomes central.

Within this framework, three interrelated dimensions of competence emerge as critical for assessment: transparency, verification and validation, and engineering judgment.

The first is transparency, which refers to the extent to which students explicitly document and communicate their use of AI tools. Transparency includes not only identifying where AI was used, but also articulating the purpose of that use, the nature of the outputs generated, and the modifications applied. This dimension is essential for establishing accountability, as it allows instructors and evaluators to distinguish between student-generated reasoning and AI-assisted contributions.

The second dimension is verification and validation, which captures the rigor with which students evaluate AI-generated outputs. This includes testing functionality, comparing outputs against expected behavior, cross-referencing with authoritative sources such as technical documentation, and identifying inconsistencies or failure modes. Verification reflects a student's ability to recognize that AI-generated outputs are not inherently reliable and must be critically examined. In this sense, validation is not merely a technical activity but a core learning process through which students engage with uncertainty and develop deeper understanding.

The third dimension is engineering judgment, defined as the ability to make informed decisions under conditions of partial information and to justify those decisions with evidence. In AI-augmented environments, engineering judgment includes determining when AI outputs are appropriate, when they require modification, and when they should be rejected entirely. It also includes the ability to integrate multiple sources of information, reconcile conflicting evidence, and communicate reasoning clearly to others. This dimension reflects the shift from execution-based competence to decision-based competence, where the quality of reasoning becomes as important as the correctness of outcomes.

Table 2. Assessment Dimensions for AI-Augmented Experiential Learning

Assessment Dimension	Description	Observable Evidence
Transparency	Clear documentation of AI use and role in workflow	AI-use disclosures, documented prompts, revision logs
Verification and Validation	Testing and critical evaluation of AI outputs	Test results, comparison with specifications, debugging artifacts
Engineering Judgment	Decision-making under uncertainty and justification of choices	Design rationale, tradeoff analysis, rejection or modification of AI outputs

As summarized in Table 2, these dimensions make visible the processes through which students engage with AI and provide a structured basis for evaluating competence in AI-augmented environments

The three dimensions redefine the basis for assessment in experiential learning. Rather than evaluating isolated artifacts, assessment must capture how students navigate the interaction between human reasoning and machine-generated outputs. This requires not only changes to grading criteria but also to the design of assignments and learning activities. For example, requiring students to document AI use, justify design decisions, and provide evidence of validation can make these processes visible and assessable. Similarly, incorporating reflective components that prompt students to analyze their interaction with AI can provide insight into their reasoning and learning processes.

Importantly, the emphasis on transparency, validation, and judgment aligns closely with the competencies observed to differentiate higher-performing teams in this study. Students who engaged in systematic validation and maintained clear documentation of AI use were consistently more effective in diagnosing failures, refining designs, and articulating their decisions. This suggests that assessment frameworks grounded in these dimensions are not only theoretically appropriate but also empirically supported. Survey responses further support the importance of these dimensions. Students who reported routinely validating AI-generated outputs also described greater confidence in their engineering decisions and demonstrated stronger awareness of AI limitations, reinforcing the central role of validation and engineering judgment in AI-mediated experiential learning.

More broadly, this shift in assessment reflects a change in how engineering expertise is defined. In AI-mediated environments, expertise is no longer characterized solely by the ability to produce solutions independently, but by the ability to critically evaluate, adapt, and take responsibility for solutions generated in collaboration with intelligent systems. Assessment practices that capture this shift are essential for ensuring that experiential learning remains aligned with the evolving demands of engineering practice.

6. Case Study

The representative case aligns closely with the broader survey findings. Students repeatedly described AI as an effective mechanism for accelerating implementation while simultaneously emphasizing the need for verification, particularly in contexts involving hardware integration and system-level design. The case therefore illustrates a recurring pattern identified across both the qualitative survey responses and faculty observations.

To illustrate how the redistribution of cognitive effort manifests in practice, this section presents a representative case drawn from both an advanced embedded systems course and a corresponding internship-for-credit placement. This case is not an isolated example, but rather reflects a pattern observed across multiple teams and contexts and is used here to provide a concrete instantiation of the broader findings described in the previous section.

In this case, a student team was tasked with developing firmware for a sensor-based data acquisition system that required integration of hardware interfaces, timing constraints, and data communication protocols. Early in the project, the team used a generative AI tool to produce an initial implementation of the firmware, including routines for sensor initialization, data sampling, and communication with an external interface. The use of AI enabled the team to rapidly generate a functional baseline system, significantly reducing the time required to achieve initial functionality. As a result, the team was able to shift its attention earlier than expected toward system integration and testing.

However, during subsequent testing, the system exhibited intermittent and difficult-to-reproduce failures, including inconsistent data readings and unexpected resets. Initial attempts to debug the issue were unsuccessful, as the AI-generated code appeared syntactically correct and functioned under limited test conditions. This led to a period of uncertainty in which the team struggled to reconcile observed behavior with their understanding of the system.

A more detailed investigation revealed that the AI-generated code contained implicit assumptions about hardware configuration that were not valid for the specific microcontroller platform being used. In particular, the code configured timing and interrupt priorities in a manner that was compatible with similar devices but not with the exact hardware in use. These discrepancies were not immediately visible in the generated code and only became apparent when the system was subjected to realistic operating conditions.

Resolving the issue required the team to engage in systematic validation and iterative refinement. This process included cross-referencing the AI-generated implementation with device-specific documentation, conducting targeted hardware-level tests, and incrementally modifying the code to align with system constraints. Through this process, the students developed a deeper understanding of both the system architecture and the limitations of the AI tool they were using. Importantly, the majority of the team’s effort during this phase was not spent generating new code, but rather interpreting existing code, identifying inconsistencies, and making informed decisions about how to modify it.

A similar pattern was observed during the student's internship-for-credit experience, where AI tools were used to support development tasks in a professional setting. In that context, AI-generated solutions were initially accepted due to time pressures and apparent correctness but required subsequent validation when deployed within larger systems. As in the academic setting, critical learning occurred during the process of diagnosing failures, validating assumptions, and refining solutions rather than during initial implementation.

This case exemplifies the broader shift identified in the results: while AI accelerates the generation of candidate solutions, it simultaneously introduces hidden assumptions that only become visible during validation and integration. The educational significance of this shift lies in the fact that the most cognitively demanding and meaningful learning occurs not during the production of solutions, but during their evaluation and refinement. In this sense, the case provides concrete evidence that the dominant site of learning in AI-augmented experiential environments has moved from execution to validation.

Moreover, the case highlights the importance of transparency and traceability in AI use. The difficulty the team initially experienced in diagnosing the issue was directly related to their limited understanding of how the AI-generated code was constructed. Once the team began explicitly documenting AI outputs and their subsequent modifications, their ability to reason about system behavior improved significantly. This observation reinforces the broader finding that structured validation and documentation practices are closely associated with improved performance.

This case demonstrates that AI-mediated experiential learning is characterized not by reduced complexity, but by a reorganization of where that complexity resides. The challenges faced by students are no longer primarily located in generating solutions, but in interpreting, validating, and taking responsibility for those solutions within complex systems. As such, the case provides a concrete illustration of how the AI-Augmented Experiential Learning Ecosystem operates in practice and why validation and engineering judgment have become central to learning in these environments.

7. Implications for Engineering Education and Curriculum Design

The findings of this study have implications that extend beyond individual courses to the broader structure and purpose of experiential learning in engineering education. As generative AI becomes embedded in engineering workflows, the competencies required of students are shifting in ways that challenge longstanding assumptions about how expertise is developed and demonstrated. Experiential learning environments, which have traditionally emphasized direct engagement in execution, must now be reconsidered in light of the changing relationship between human cognition and automated systems.

A central implication is that experiential learning can no longer be defined primarily in terms of artifact production. When AI systems contribute significantly to the generation of solutions, the educational value of experiential activities is no longer located in the act of producing those solutions, but in the processes through which students interpret, validate, and integrate them. This shift suggests that the core purpose of experiential learning is evolving from developing executional proficiency to cultivating evaluative and decision-making capabilities. In this context, learning environments must be designed not only to support the creation of solutions, but also to foreground the critical examination of those solutions.

The survey findings suggest that students themselves recognize this progression. Early use of AI is associated primarily with productivity and exploration, whereas more advanced learners increasingly describe AI as a tool whose value depends on careful verification and interpretation. This progression closely mirrors the conceptual model proposed in this study and provides empirical support for designing curricula that intentionally cultivate validation and engineering judgment over time.

This reframing has important consequences for how curricula are structured across the undergraduate experience. Rather than treating AI as an external tool introduced in isolated contexts, it must be integrated as a persistent element of the learning environment. Early-stage courses play a critical role in introducing students to AI as a means of exploration, enabling them to engage with complex problems without being constrained by implementation barriers. Prior work has similarly shown that students perceive generative AI not only as a productivity tool but also as a mechanism for improving access to academic support and increasing confidence when engaging with challenging engineering content [14]. However, as students progress, the emphasis must shift toward developing the ability to interrogate AI-generated outputs, identify limitations, and reason about system behavior under conditions of uncertainty. In this sense, the progression across courses is not simply an increase in technical complexity, but a shift in the nature of cognitive engagement.

Workplace-integrated experiences, such as internships for academic credit, further amplify these dynamics by situating students in environments where the consequences of error are more immediate and where expectations for accountability are more explicit. In these contexts, students must navigate the tension between efficiency and reliability, often relying on AI tools to accelerate development while simultaneously ensuring that outcomes meet professional standards. The findings of this study suggest that these experiences play a critical role in reinforcing the importance of validation, traceability, and engineering judgment, as students encounter firsthand the limitations of AI-generated solutions in real-world systems.

At a broader level, these shifts point to a redefinition of engineering expertise itself. In AI-mediated environments, expertise is no longer characterized solely by the ability to independently produce solutions, but by the ability to critically evaluate, adapt, and take responsibility for solutions generated in collaboration with intelligent systems. This redefinition aligns with trends in professional practice, where engineers are increasingly expected to function as supervisors of automated processes, responsible for ensuring correctness, reliability, and ethical use.

The AI-Augmented Experiential Learning Ecosystem model provides a framework for understanding how these competencies develop across contexts and over time. The model highlights the importance of continuity and alignment across learning environments by conceptualizing experiential learning as a distributed system rather than a collection of isolated activities. This perspective supports the design of curricula that intentionally develop competencies related to validation and judgment, rather than assuming that such competencies will emerge implicitly through exposure to complex tasks.

Finally, the implications of this work extend to how educational institutions conceptualize the relationship between learning and practice. As AI continues to evolve, the boundary between academic learning environments and professional engineering contexts is becoming increasingly permeable. Students are not only preparing for AI-mediated practice; they are already participating in it. As a result, experiential learning must be designed to reflect the realities of this participation, ensuring that students develop the ability to engage critically and responsibly with AI systems from the outset of their education. These observations complement earlier work demonstrating that students frequently view generative AI as a source of inclusive academic support, particularly when navigating unfamiliar concepts or language-intensive engineering tasks [14].

These implications suggest that the integration of AI is not simply a technological enhancement to existing educational practices, but a catalyst for rethinking the foundations of experiential learning. By shifting the focus from execution to validation, and from production to interpretation, engineering education can remain aligned with the evolving demands of professional practice while preserving its core commitment to developing deep and transferable expertise.

8. Limitations

The findings of this study should be interpreted in light of several methodological and contextual considerations that both define the scope of the analysis and suggest directions for future work. First, the study is grounded in a mixed-methods, practice-based research approach conducted within a single institutional context and within the domain of electrical and computer engineering. While this design enables a detailed and contextually rich understanding of how students engage with AI across multiple experiential learning environments, it does not aim to produce statistically generalizable results. Instead, the intent is to identify recurring patterns and mechanisms that can inform theory and guide further investigation.

Second, the analysis relies on a combination of project artifacts, structured AI-use disclosures, and observational data rather than controlled experimental measures. This approach is appropriate for capturing authentic student behavior in complex learning environments, but it also introduces variability in how data are generated and interpreted. For example, self-reported AI use may be influenced by students' awareness of expectations or their ability to accurately recall and articulate their interactions with AI systems. However, the use of multiple data sources, including artifacts and instructor observations, provides a degree of triangulation that strengthens the credibility of the findings.

Third, the rapid evolution of AI tools presents an inherent limitation for any study in this domain. The capabilities, interfaces, and usage patterns associated with generative AI are changing quickly, and the specific tools used by students during the study period may differ from those available in future contexts. As a result, the findings should be interpreted not as tied to a particular technology, but as reflective of broader patterns in how AI mediates cognitive effort and learning processes. The emphasis on underlying mechanisms, such as validation, traceability, and judgment, is intended to ensure that the insights remain relevant even as specific tools evolve.

Finally, while the study incorporates data from both academic and workplace-integrated environments, the representation of professional contexts is based primarily on internship experiences and associated feedback rather than on direct, systematic data collection from industry settings. Expanding this work to include more structured and longitudinal data from professional engineering environments would further strengthen the connection between educational practice and workplace expectations.

These limitations do not diminish the contribution of the study; rather, they clarify its scope and highlight opportunities for future research. In particular, there is a need for multi-institutional studies, quantitative analyses of learning outcomes, and deeper investigation into how AI-mediated practices vary across disciplines and professional domains. Such work would build on the conceptual and empirical foundation established here to further refine our understanding of experiential learning in the age of artificial intelligence.

9. Conclusions

The integration of generative artificial intelligence into engineering practice is fundamentally reshaping experiential learning by redistributing cognitive effort and redefining the nature of engineering work. This study demonstrates that, across a range of academic and workplace-integrated contexts, the dominant site of learning shifts from the production of solutions to the validation and interpretation of AI-generated outputs. Rather than simplifying the learning process, AI transforms it by concentrating cognitive effort in activities that require critical evaluation, system-level reasoning, and decision-making under uncertainty.

This paper provides a framework for understanding how these shifts unfold across multiple contexts and over time by introducing the AI-Augmented Experiential Learning Ecosystem model. The model highlights that learning in AI-mediated environments is not confined to isolated tasks or courses but emerges through the dynamic interaction between human cognition and machine-generated outputs across phases of engineering work. In doing so, it extends existing conceptions of experiential learning by explicitly accounting for the role of AI as a cognitive collaborator.

The findings further suggest that experiential learning in this context is no longer defined by direct execution alone, but by the ability to supervise, validate, and integrate machine-augmented work. This shift has important implications for how engineering competence is conceptualized, developed, and assessed. Competence is increasingly characterized not by the ability to independently generate solutions, but by the capacity to critically engage with those solutions, identify their limitations, and take responsibility for their outcomes.

More broadly, this work underscores the need to align engineering education with the evolving realities of professional practice. As AI becomes an integral component of engineering workflows, educational environments must reflect the ways in which engineers interact with automated systems in practice. This requires not only the integration of AI tools into curricula, but also a reorientation of learning goals toward validation, transparency, and judgment as central competencies.

Ultimately, the contribution of this paper lies in making explicit a shift that is already underway. It establishes a foundation for future research on design, assessment, and scaling of engineering education in AI-mediated environments by redefining experiential learning as the process of supervising and validating machine-augmented work. In doing so, it positions experiential learning not as diminished by AI, but as reconfigured in ways that are more closely aligned with the demands of contemporary engineering practice.

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Appendix A: Student AI-Use Disclosure Template

To promote transparency, accountability, and reflective practice, students were required to document their use of artificial intelligence tools throughout their projects. The following template was used across multiple experiential learning contexts, with minor adaptations depending on course structure and expectations.

Project Title:

Team Members:

AI Tool(s) Used:
Students identify the specific AI tools used, including platform names and versions where applicable.

Purpose of AI Use:
Students describe the intended purpose of AI use, such as code prototyping, debugging assistance, documentation support, or conceptual exploration.

Stage of Use:
Students indicate when AI was used within the project lifecycle, including problem framing, implementation, testing, or documentation.

Description of AI Contribution:
Students provide a detailed account of the outputs generated by AI and the prompts or inputs used to produce those outputs.

Verification and Validation:
Students explain how AI-generated outputs were tested, reviewed, and validated. This includes any comparisons to expected behavior, use of documentation, or experimental testing.

Human Modifications and Decisions:
Students describe how AI-generated outputs were modified, refined, or rejected. They explain the rationale behind these decisions and the role of engineering judgment.

Reflection on Impact:
Students reflect on how AI use influenced their learning and project outcomes, including both benefits and challenges.

Students were informed that AI use was permitted and encouraged when appropriately documented and validated. Undocumented or uncritical reliance on AI was considered a limitation in performance evaluation.