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Integrating Artificial Intelligence into Undergraduate Electrical and Computer Engineering Education: Opportunities and Challenges

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Integrating Artificial Intelligence into Undergraduate Electrical and Computer Engineering Education: An Assessment-Centered Framework for Preserving Demonstrable Competence

Abstract

The integration of generative artificial intelligence (AI) tools into undergraduate electrical and computer engineering (ECE) education is fundamentally reshaping how students solve problems, produce artifacts, and demonstrate learning. Generative systems capable of producing code, analytical solutions, and technical explanations in real time are now routinely embedded in student workflows. While these tools expand access to academic support and improve task completion efficiency, they introduce a critical challenge: correct outputs can no longer be assumed to reflect underlying understanding. Prior research in engineering and higher education reveals that AI-assisted environments can increase performance while simultaneously obscuring the reasoning processes that traditionally serve as evidence of competence [1], [2].

This study presents a multi-year, practice-based case study of AI integration within an ABET-accredited ECE program, incorporating survey-informed exploratory data from undergraduate students across multiple ECE-related course contexts collected through April 2026 (N = 178). Results show that 90.8% of respondents reported at least some use of ChatGPT in a course context, with 72.3% reporting occasional, weekly, or daily use. Students most commonly reported using ChatGPT for concept explanations (76.6%), coding/debugging (58.1%), studying for exams (55.7%), and homework problems (41.3%). Students also reported high levels of self-directed engagement with AI-generated outputs: 89.7% reported asking follow-up questions to better understand concepts, 86.3% reported focusing on understanding the solution rather than simply obtaining the answer, 86.4% reported critically evaluating responses, and 72.7% reported verifying answers using other resources. At the same time, 25.6% reported sometimes relying on ChatGPT without fully understanding the solution, and 39.2% reported sometimes struggling to determine whether ChatGPT responses are correct.

We argue that these findings reflect a deeper structural issue in engineering education, the artifact–competence divergence problem, in which students may generate correct or useful solutions without consistently demonstrating the capacity to evaluate, verify, or justify those solutions under changing conditions. To address this challenge, the paper introduces and utilizes an assessment-centered framework grounded in engineering adequacy judgment, which characterizes competence as the ability to determine when available evidence is sufficient to justify action under uncertainty. This framing aligns with established perspectives in engineering practice that emphasize verification, reasoning, and responsible decision-making under incomplete information [4], [5].

The findings demonstrate that AI availability alone does not determine whether AI functions as a learning support or a substitute for understanding. Rather, the critical issue is whether assessment practices make reasoning, verification, and judgment visible. In artifact-based assessment environments, AI can support the production of correct outputs without requiring demonstrable competence; in explanation- and verification-centered environments, AI use is constrained by the

need to justify reasoning. This result reframes AI integration as an evidentiary validity problem, shifting the central educational question from whether students can produce correct answers to whether those answers can still serve as credible evidence of competence.

1. Introduction

Engineering education is at a critical inflection point as generative artificial intelligence (AI) tools become embedded in undergraduate electrical and computer engineering (ECE) learning environments. Students now routinely use AI systems to generate code, solve circuit problems, interpret signals, and produce technical documentation. Unlike earlier educational technologies, generative AI systems do not merely provide access to information; they actively participate in the problem-solving process by producing complete solutions, structured explanations, and design alternatives in real time [1], [2].

While the adoption of AI has generated significant interest in their potential to improve access to support and increase efficiency, it also introduces a fundamental challenge for engineering education. Historically, instructors have relied on student artifacts, correct calculations, functioning programs, and well-structured reports, as evidence of competence. In AI-enabled environments, however, these artifacts may no longer reliably reflect independent student understanding. Students can now produce correct or highly polished outputs with reduced engagement in the reasoning processes that traditionally underpinned those outputs. As a result, the relationship between artifact correctness and demonstrable competence is no longer stable.

This paper advances a central claim: generative AI disrupts the evidentiary foundations of engineering education by breaking the historical link between artifact correctness and demonstrable competence. In AI-enabled environments, correct outputs can no longer be treated as reliable evidence of understanding, requiring a fundamental shift in how learning is evaluated. In doing so, it exposes what we term the artifact–competence divergence problem, a condition in which students can generate correct solutions without demonstrating the ability to explain, adapt, verify, or justify those solutions under changing conditions. This divergence is not simply a matter of academic integrity or improper tool use; it reflects a deeper epistemic shift in how engineering knowledge is produced and evaluated.

Exploratory data from this study make this divergence visible in a more nuanced way. Among 178 respondents, 90.8% reported at least some use of ChatGPT in a course context, and 72.3% reported using it occasionally, weekly, or daily. Students most frequently reported using ChatGPT for concept explanations, coding/debugging, exam preparation, and homework support. These results suggest that ChatGPT is not a peripheral tool but a regular component of many students' academic workflows. At the same time, the survey also reveals tensions central to the artifact–competence divergence problem. Although students report high levels of interaction with AI-generated outputs, including asking follow-up questions, checking work, and verifying answers, a substantial minority also report relying on ChatGPT without fully understanding the solution or struggling to determine whether its responses are correct. These findings are consistent with prior research on automation bias and cognitive offloading, which shows that users of AI-assisted systems may accept outputs without sufficient critical evaluation, particularly when those outputs appear fluent and authoritative [3]. In educational contexts, this creates a situation in which performance and access to support may improve while the depth and observability of underlying understanding remain uncertain.

The significance of this divergence is particularly acute in engineering. Engineering is not merely concerned with producing correct answers; it is fundamentally concerned with authorizing action under uncertainty. Engineers must determine whether a model is adequate for design, whether simulation results are reliable, whether a system meets safety and performance requirements, and whether remaining uncertainty is acceptable given the potential consequences of failure. These judgments are central to professional practice and are explicitly reflected in accreditation frameworks such as ABET, which emphasize problem solving, design under constraints, communication, and ethical responsibility [4]. Foundational work in engineering education similarly highlights the importance of preparing students for decision-making in real-world, uncertain contexts [5].

From an educational perspective, this raises a critical question: can students still develop the capacity to determine when available evidence is sufficient to justify engineering action in AI-enabled environments? If not, engineering education risks producing graduates who can generate technically correct solutions but cannot assess their adequacy in real-world contexts. This concern reflects a shift from evaluating what students produce to evaluating how they reason about what they produce.

To address this challenge, this paper reframes AI integration as an evidentiary validity problem**.** The central issue is no longer whether students use AI, but whether educational systems can still produce credible evidence of what students understand and can justify under uncertainty. Within this framing, assessment becomes the primary mechanism for preserving competence. When assessment emphasizes explanation, adaptation, and verification, students are required to engage in the reasoning processes that define engineering practice. When assessment relies primarily on final artifacts, AI can substitute for those processes, obscuring underlying gaps in understanding.

This paper introduces and utilizes an assessment-centered framework grounded in engineering adequacy judgment**,** which defines competence in terms of students' ability to determine when available evidence is sufficient to justify action under uncertainty. By focusing on adequacy rather than correctness, this framework aligns more closely with the epistemic and practical demands of engineering practice.

The contributions of this paper are threefold. First, it identifies and defines the artifact–competence divergence problem as a central challenge in AI-enabled engineering education. Second, it introduces an assessment-centered framework that translates into observable engineering behaviors competence as evidence sufficiency under uncertainty. Third, it provides empirical and practice-based evidence that assessment design, not AI availability, is the primary determinant of whether AI supports or obscures learning.

These contributions shift the conversation about AI in engineering education. The central challenge is no longer whether students can produce correct answers, but whether they can determine when those answers are sufficiently justified to support responsible engineering action.

2. Background and Related Work

The integration of generative artificial intelligence (AI) into engineering education sits at the intersection of several well-established research domains, including AI-assisted learning, engineering pedagogy, and human–AI interaction. While each of these areas has developed independently, their convergence reveals a critical and underexplored challenge: how learning should be evaluated when tools can produce correct outputs without requiring full conceptual engagement. This section synthesizes relevant literature to situate the present study and to identify the gap it addresses.

2.1 Generative AI and Learning in Higher Education

Generative AI systems, particularly large language models, have introduced new forms of academic support characterized by immediacy, adaptability, and interactive feedback. These systems can generate explanations, solve complex problems, and provide iterative guidance, effectively functioning as on-demand learning companions. As a result, they have the potential to improve access to support, reduce barriers to engagement, and enable students to continue working through challenges without interruption [2].

However, the same characteristics that make generative AI powerful also introduce new risks. AI-generated outputs are often fluent and plausible even when incomplete or incorrect, making them difficult to evaluate without prior knowledge. Kasneci et al. emphasize that while these systems can enhance learning opportunities, they also raise concerns related to reliability, bias, and uncritical acceptance of outputs [2]. More importantly, recent work has begun to shift attention from access to evaluation. Swiecki et al. argue that AI fundamentally alters the relationship between learning and assessment by enabling students to produce outputs without engaging in the reasoning processes those outputs were intended to measure [1].

This shift suggests that the primary educational impact of AI lies not in its ability to provide information, but in its capacity to change how learning is evidenced. When outputs can be generated independently of reasoning, traditional assessment methods may no longer capture the cognitive processes they were designed to evaluate.

2.2 Generative AI in Engineering Education

Within engineering education, the adoption of generative AI has been both rapid and uneven. Students increasingly use AI for programming, debugging, analytical problem solving, and design exploration, often integrating these tools into their workflows as primary sources of support. Faculty observations across engineering programs suggest that AI is frequently used as a first-access resource, particularly outside structured instructional time.

Recent research in engineering education has begun to document these emerging patterns of AI integration. Harris and Kittur's systematic review highlights both the rapid expansion of generative AI use in undergraduate engineering courses and the absence of coherent frameworks for understanding its educational impact [6]. Consistent with this, Hassani et al. report that while faculty recognize the potential benefits of AI for supporting student learning, they also express significant uncertainty about how to evaluate student work when AI contributes to the final output [7]. Together, these findings point to a growing disconnect between AI-enabled performance and the mechanisms used to assess student competence.

Across these studies, a consistent pattern emerges: AI improves efficiency and enhances the quality of student artifacts, but it introduces ambiguity in how those artifacts should be interpreted. Students may submit technically correct or highly polished work, yet instructors lack reliable indicators of whether that work reflects independent understanding. Despite recognizing this issue, existing research has largely focused on describing usage patterns rather than addressing the deeper question of how competence should be evaluated in AI-enabled environments.

2.3 Overreliance, Automation Bias, and Cognitive Offloading

A critical body of research relevant to this study examines how individuals interact with automated systems and the conditions under which they rely on those systems. Buçinca, Malaya, and Gajos demonstrate that users frequently exhibit automation bias, accepting AI-generated outputs without sufficient verification, particularly when those outputs appear confident or authoritative [3]. This phenomenon is not simply a behavioral anomaly, but a systematic feature of human–AI interaction.

In educational contexts, automation bias is closely related to cognitive offloading, where individuals rely on external systems to reduce cognitive effort. While offloading can be beneficial in certain contexts, it may also reduce engagement with underlying reasoning processes, particularly when tasks can be completed without deep conceptual processing. In engineering education, this raises a significant concern: if students rely on AI to generate solutions, they may not engage in the verification, adaptation, and reasoning processes that define engineering competence.

This issue is particularly critical because engineering practice requires more than obtaining correct results. It requires the ability to evaluate those results, test their validity, and determine their applicability under varying conditions. If AI enables students to bypass these processes, then the development of engineering judgment may be compromised.

2.4 Engineering Learning, Verification, and Demonstrable Understanding

Longstanding research in engineering education emphasizes that learning is most effective when students actively engage in reasoning, explanation, and verification. Prince's review of active learning demonstrates that students achieve deeper understanding when they are required to engage cognitively with material rather than passively receive information [8]. Similarly, Freeman et al. show that active learning approaches increase student performance across STEM disciplines by making reasoning processes more explicit [9].

In engineering contexts, verification is a vital component of this process. Engineers do not simply accept results; they test them, validate them, and assess their robustness under varying conditions. These practices are essential for ensuring that solutions are not only correct, but reliable and appropriate for real-world use.

Generative AI challenges this model by enabling students to produce correct results with reduced engagement in verification processes. As a result, the educational task shifts from ensuring that students can generate answers to ensuring that they can critically evaluate, justify, and determine the reliability of those answers. This shift aligns with broader work in engineering education that emphasizes situative learning, professional formation, and the development of engineering judgment as central to competence [10] – [12].

2.5 Emerging Concerns: AI, Integrity, and Assessment Disruption

Recent empirical studies examining generative AI in higher education further highlight concerns related to academic integrity, assessment validity, and shifts in student behavior. Cotton et al. argue that generative AI complicates traditional notions of authorship and originality, making it more difficult to distinguish between student-generated and AI-assisted work [11]. Rudolph et al. similarly suggest that generative AI may challenge the validity of traditional assessment methods by enabling students to produce acceptable outputs without demonstrating underlying understanding [12].

Additional work by Baidoo-Anu and Owusu Ansah highlights both the benefits and limitations of AI in educational settings, noting that while these systems can support learning, they also risk encouraging superficial engagement when used without critical evaluation [13]. These studies collectively reinforce the idea that AI is not simply a tool, but a force that reshapes how learning is experienced and assessed.

2.6 Gap in the Literature and Positioning of This Study

Literature reveals a clear and significant gap. Existing research has documented the rapid adoption of generative AI, identified its potential benefits, and highlighted concerns related to overreliance and assessment. However, it has not fully addressed the underlying epistemic problem: *what counts as valid evidence of competence when correct outputs can be generated without full understanding*.

Taken together, prior work points to a consistent pattern: while generative AI improves access and performance, it simultaneously weakens the link between outputs and the reasoning processes they were intended to represent. This disconnect highlights the need for frameworks that explain not only how AI is used, but how competence can still be validly inferred from student work.

This paper addresses that gap by reframing AI integration as an evidentiary validity problem. Rather than focusing on whether students use AI, it examines whether educational systems can still produce credible evidence of what students understand and can justify. In doing so, it provides a foundation for evaluating learning in AI-enabled environments while preserving the core intellectual and professional goals of engineering education through an assessment-centered framework grounded in engineering adequacy judgment.

3. Research Questions

This study is guided by four research questions that are designed to move beyond descriptive accounts of AI use and toward a structured evaluation of its implications for engineering learning, competence, and assessment. While prior work has primarily focused on how students use generative AI systems, this study emphasizes how those uses affect the relationship between performance, understanding, and the evidentiary basis of learning in electrical and computer engineering (ECE) education.

The first research question examines how undergraduate ECE students are using generative AI in coursework. This includes not only the frequency of use, but also the types of tasks for which AI is employed, such as programming, debugging, circuit analysis, and design exploration. Understanding these patterns is essential for establishing how deeply AI is embedded in student workflows and how it is reshaping the structure of problem solving. Prior research has shown that AI adoption is widespread and rapidly increasing in engineering contexts, but less attention has been given to how this use changes the sequencing and nature of student reasoning [2], [6].

The second research question investigates how AI use influences the relationship between artifact quality and demonstrable engineering competence. This question directly addresses the central problem identified in this paper, the artifact–competence divergence problem, by examining whether students' ability to produce correct outputs aligns with their ability to explain, adapt, and justify those outputs independently. Existing work in AI-assisted learning suggests that performance improvements may not correspond to equivalent gains in understanding, particularly in environments where outputs can be generated without full engagement in reasoning processes [1], [3]. This study extends that insight specifically to ECE contexts.

The third research question explores which assessment practices provide reliable evidence of student learning in AI-enabled environments. Rather than treating assessment as a neutral component of instruction, this question positions it as a central mechanism that shapes how students engage with AI and whether their learning remains visible. Prior research in engineering education has consistently shown that active and reasoning-centered assessment practices improve conceptual understanding and make learning processes observable [8], [9]. This study examines whether those principles remain effective when AI systems are widely available.

The fourth research question considers how ABET-aligned structures can support responsible AI integration while maintaining the evidentiary validity of engineering education. This includes examining how existing outcomes related to problem solving, design, communication, and professional responsibility can be interpreted and used in contexts where AI contributes to student work. As engineering practice increasingly involves interaction with complex tools and systems, the ability to evaluate and justify solutions becomes central to professional competence [4], [5]. This question therefore connects classroom practices to broader expectations of engineering education and accreditation.

These research questions enable a multi-level analysis that connects student behavior, cognitive processes, and institutional practices. The study provides a structured approach for understanding how engineering education can adapt to AI-enabled environments without compromising the development of demonstrable competence and engineering judgment by linking patterns of AI systems use to assessment design and accreditation frameworks.

4. Conceptual Framework

4.1 From Artifact Correctness to Demonstrable Competence

Engineering education has traditionally operated under the assumption that correct artifacts, whether circuit analyses, functional code, or technical reports, provide reliable evidence of student competence. This assumption has been largely valid in pre-AI contexts, where producing correct outputs required students to engage with underlying principles, perform analytical reasoning, and iteratively refine their solutions. In such settings, the artifact itself served as a proxy for the reasoning processes that generated it.

Generative AI fundamentally disrupts this relationship. Students can now produce correct or highly polished outputs with reduced engagement in the reasoning processes that traditionally underpinned those outputs. As a result, correctness can no longer be treated as a sufficient indicator of competence. This shift necessitates a redefinition of how competence is understood and evaluated in engineering education.

In this study, demonstrable competence is defined as the ability to explain, adapt, verify, and justify engineering solutions independently of AI assistance. This definition reflects observable behaviors that indicate meaningful understanding rather than mere production of output. It aligns with prior work in engineering education emphasizing the importance of active engagement and reasoning in developing conceptual understanding [8], [9].

4.2 Engineering Judgment Under Uncertainty

A defining characteristic of engineering practice is that decisions must be made under conditions of uncertainty. Engineers rarely operate with complete information; instead, they must determine whether available evidence is sufficient to support action. This includes evaluating whether models are adequate, whether simulations are reliable, and whether system behavior is sufficiently understood to justify design or implementation decisions.

This study extends that perspective into the educational domain by introducing the concept of engineering adequacy judgment. Adequacy judgment refers to the ability to determine when a solution is not only correct, but sufficiently verified, sufficiently understood, and sufficiently reliable to support action in a given context. It involves evaluating assumptions, identifying uncertainties, and deciding whether additional evidence is required before proceeding.

In ECE contexts, adequacy judgment is expressed in concrete and discipline-specific ways. A student working on a circuits problem must determine whether a computed solution remains valid when component values change or when non-ideal effects are introduced. In embedded systems, a student must evaluate whether code that compiles and runs is robust to timing variations, hardware constraints, and edge cases. In signal processing, a student must assess whether results obtained under ideal conditions remain meaningful in the presence of noise, distortion, or changing input characteristics.

These judgments cannot be reduced to correctness alone. They require explicit reasoning about uncertainty and reliability, which are central to engineering practice and are reflected in accreditation expectations emphasizing problem solving, design, and professional responsibility [4], [5].

4.3 Competence as Observable Engineering Behavior

This framework translates competence into observable engineering behaviors that reflect both understanding and judgment. These behaviors include the ability to reconstruct solutions independently, adapt them under changing conditions, verify their correctness using appropriate engineering methods, and justify the assumptions and decisions involved.

Reconstruction refers to the ability to reproduce or derive a solution without reliance on external tools. Adaptation involves modifying a solution when parameters, constraints, or operating conditions change. Verification requires testing or validating results through simulation, measurement, or analytical checks. Justification involves explaining the reasoning behind a solution, including its assumptions, limitations, and applicability.

In addition to these established behaviors, this framework emphasizes adequacy judgment as a critical dimension of competence. Adequacy judgment involves determining whether available evidence is sufficient to proceed. For example, a student may generate a correct circuit solution using AI, but competence is demonstrated only if the student can evaluate whether that solution has been sufficiently validated and whether it can be trusted under relevant conditions.

This emphasis reflects the broader shift identified in this paper: from evaluating outputs to evaluating the reasoning processes that support those outputs. It also aligns with research on human–AI interaction, which shows that users must actively evaluate system outputs to avoid overreliance and ensure reliability [3].

4.4 The Role of AI in Supporting or Obscuring Competence

Within this framework, AI is understood as a tool whose impact depends on how it interacts with observable engineering behaviors. AI can support learning when it enables exploration, provides alternative explanations, and facilitates iterative refinement. In such cases, it can function as a scaffold that enhances engagement with complex concepts and supports deeper understanding.

However, AI can also obscure competence when it allows students to bypass key reasoning processes. When solutions are generated without requiring reconstruction, adaptation, or verification, the resulting outputs may appear correct while concealing gaps in understanding. This is particularly problematic in engineering contexts, where correctness must be accompanied by reliability and justification.

The central issue is therefore not whether AI is used, but whether its use preserves the conditions under which competence can be demonstrated. This depends largely on how tasks are structured and how learning is evaluated. If assessment does not require reasoning and verification, AI can substitute for those processes. If assessment requires them, AI becomes a tool that supports rather than replaces learning.

4.5 Implications for Assessment and Evidence of Learning

The conceptual framework leads to a clear implication: assessment must be designed to capture demonstrable competence in ways that remain valid in the presence of AI. This requires shifting from artifact-based evaluation to evidence-based evaluation, where the focus is on reasoning, verification, and judgment.

In ECE contexts, this involves designing assessments that require students to explain how solutions change under modified conditions, debug systems in real time, validate results through simulation or measurement, and justify design decisions in terms of assumptions and constraints. It also involves asking students to identify what remains uncertain and to explain why available evidence is sufficient or insufficient to proceed.

Educators can ensure that AI-supported work still provides credible evidence of learning by aligning assessment with observable engineering behaviors. More importantly, they can preserve the development of engineering judgment, which is essential for both educational outcomes and professional practice.

5. Methods

5.1 Research Design

This study employs a qualitative, practice-based case study design supplemented by survey-informed exploratory data. The objective of this design is not to establish causal relationships, but to identify and interpret patterns that illuminate how generative AI influences learning, competence, and assessment in ECE education.

A case study approach is particularly appropriate given the nature of the research problem. The use of AI in educational contexts is not uniform or controlled; rather, it is embedded within authentic instructional environments and shaped by course design, instructor expectations, and student behavior. Instead of isolating variables, this study examines how AI interacts with existing pedagogical structures in real-world settings. This approach enables a more comprehensive understanding of how AI influences both student performance and the evidentiary basis of learning, consistent with prior research emphasizing the importance of context in engineering education studies [10].

The inclusion of survey data provides an additional layer of insight by capturing student-reported behaviors and perceptions. While these data are exploratory and not intended for statistical generalization, they serve as an important complement to observational and artifact-based evidence, enabling triangulation across multiple data sources.

5.2 Context and Setting

The study is situated within an ABET-accredited undergraduate ECE program and includes data from multiple course contexts selected to represent distinct dimensions of engineering learning. These include analytically focused courses such as circuits, programming-intensive courses such as embedded systems, and design-oriented courses such as senior capstone projects.

These contexts were chosen intentionally to capture variation in how AI is used across different types of engineering tasks. Circuits courses emphasize mathematical modeling, derivation, and analytical reasoning. Embedded systems courses focus on implementation, debugging, and interaction with hardware constraints. Design courses require integration of multiple subsystems, consideration of real-world constraints, and iterative decision-making under uncertainty. By examining AI use across these varied contexts, the study is able to identify patterns that are not limited to a single instructional setting.

5.3 Participants

Participants in the study include undergraduate students enrolled in ECE and ECE-related engineering course contexts. The survey dataset includes responses from N = 178 students. The sample included students across academic levels, with most respondents identifying as sophomores, juniors, or seniors. Among respondents who reported academic level, 53 identified as sophomores, 56 as juniors, and 53 as seniors, with additional responses from first-year, graduate, and transitional academic-level students. Approximately 72.5% of respondents identified their major as electrical engineering, computer engineering, or a closely related ECE field, while the remaining respondents represented computer science and other engineering or STEM majors enrolled in relevant course contexts.

Students were not selected based on AI usage; rather, AI use emerged naturally as part of their coursework. This reflects the current educational reality in which AI adoption is widespread, often self-directed, and not confined to specific assignments or courses. As a result, the data capture authentic patterns of AI use rather than behavior constrained by experimental design.

5.4 Data Sources

Data for this study were collected from multiple sources to support triangulation and enhance the credibility of findings. These sources include student survey responses, course artifacts, instructor observations, and instructional materials. Survey responses captured patterns of AI use, access to support, confidence, self-reported evaluation behavior, perceived learning benefits, and concerns about correctness or overreliance. Course artifacts included problem solutions, code submissions, and design documentation. Instructor observations documented discrepancies between artifact quality and student explanation during discussions, reviews, and assessments. Instructional materials included assignment design and assessment structures.

Each data source provides a distinct perspective on the research problem. Survey responses offer insight into how students perceive and report their use of AI. Course artifacts provide evidence of performance and output quality. Instructor observations capture the relationship between outputs and demonstrated understanding. Instructional materials reveal how assessment expectations shape student behavior.

The combination of these sources allows for a more robust interpretation of results than any single source alone. In particular, it enables the study to examine not only what students produce, but how they reason about what they produce, which is central to the concept of demonstrable competence.

5.5 Survey Design and Implementation

The survey instrument was designed to align with the research questions and conceptual framework while capturing students' actual patterns of ChatGPT use in course contexts. Survey items addressed frequency of use, course context, types of tasks supported by ChatGPT, access to help, interaction strategies, critical evaluation, verification behavior, perceived conceptual understanding, confidence, engagement, belonging, hesitation to seek help, reliance without full understanding, and difficulty determining correctness. The survey also included open-ended items asking students to describe the main benefits and concerns associated with using ChatGPT for coursework.

Responses were collected using a combination of Likert-scale items, categorical selections, multi-select items, and open-ended responses. Because the instrument asked specifically about ChatGPT, the results are interpreted as evidence of student interaction with a widely used generative AI system rather than as a comprehensive measure of all possible AI tools.

The survey data reflect self-reported behavior and perception rather than direct observation of underlying cognitive processes. Accordingly, these data provide insight into how students interpret and describe their use of AI, but do not independently verify the depth of their reasoning or the rigor of their evaluation practices. This distinction is critical, as self-reported engagement may not correspond to demonstrable competence. Prior research in human–AI interaction has shown that users often overestimate their level of understanding and verification when interacting with automated systems, particularly when outputs appear fluent and authoritative [3].

5.6 Analytical Approach

Analysis proceeded in two complementary stages: descriptive and interpretive.

The descriptive analysis focused on identifying overall patterns in AI use, including frequency of use, types of tasks, access-related perceptions, interaction strategies, self-reported evaluation behavior, confidence, engagement, and concerns. Percentages were calculated using valid responses for each item, since missing responses varied slightly across questions. Open-ended responses were reviewed for recurring themes, including access to help, concept explanation, efficiency, verification, incorrect outputs, hallucinations, and overreliance.

The interpretive analysis applied the conceptual framework of demonstrable competence and engineering adequacy judgment to evaluate the relationship between performance, reported learning support, and evidence of understanding. Specifically, the analysis examined how student-reported AI use aligned with behaviors indicative of competence, such as explanation, adaptation, verification, justification, and evaluation of reliability.

Rather than treating survey responses as definitive evidence of learning, the analysis uses them as indicators that, when combined with artifacts and observations, reveal broader trends. This approach allows the study to move beyond surface-level description and toward explanation of how AI affects the evidentiary basis of engineering education. It is consistent with prior research emphasizing the need to interpret educational data within conceptual frameworks that account for reasoning and learning processes [1].

5.7 Methodological Limitations

Several limitations of this study should be acknowledged. First, the survey data are exploratory and rely on self-reported responses, which may not fully capture actual behavior. Students may overestimate their level of understanding or the extent to which they engage in verification processes. This limitation is well-documented in research on cognitive offloading and human–AI interaction, where perceived engagement does not always align with observed behavior [3].

Second, the survey focuses specifically on ChatGPT. Although ChatGPT is a prominent generative AI system and is frequently used as a representative tool in student workflows, the findings should not be interpreted as capturing all possible forms of AI use.

Third, the study is conducted within a single institutional context, which may limit generalizability. However, the consistency of observed patterns with broader literature suggests that the findings are not unique to this setting.

Finally, the study does not attempt to quantify learning outcomes or establish causal relationships. Instead, it focuses on identifying patterns that raise important questions about how competence is evaluated in AI-enabled environments. Despite these limitations, the combination of multiple data sources and alignment with established research provides a strong basis for the study's conclusions.

These methods provide the basis for examining how AI affects both performance and the evidentiary visibility of competence.

6. Survey Results

To complement qualitative observations and course-based evidence, a survey was administered to undergraduate students across multiple ECE and ECE-related course contexts, including circuits, embedded systems, electronics design, and senior capstone. The dataset includes responses from N = 178 students, providing a broad view of how ChatGPT is being integrated into student workflows and how students perceive its impact on learning, access to support, confidence, engagement, and evaluation behavior.

The results indicate that ChatGPT use is widespread, although the actual frequency pattern is more nuanced than the earlier illustrative version of the paper suggested. Among students who responded to the frequency item, 90.8% reported using ChatGPT at least rarely in a course context, while 72.3% reported using it occasionally, weekly, or daily. Weekly or daily use was reported by 40.5% of valid respondents. These findings indicate that ChatGPT is not universally used at high frequency by all students, but it is nevertheless a common and recurring resource in undergraduate engineering coursework.

Students reported using ChatGPT across several academic tasks. Among valid responses to the multi-select task-use item, the most common use was concept explanation, reported by 76.6% of respondents. Coding and debugging were reported by 58.1%, studying for exams by 55.7%, and homework problems by 41.3%. Smaller proportions reported using ChatGPT for lab reports (13.2%) and design projects (11.4%). These results show that students are not using ChatGPT only as a coding tool or writing aid; rather, they are using it most frequently as a conceptual support resource, particularly when they need explanations, clarification, or help moving forward when stuck.

The survey also shows that students perceive ChatGPT as an accessible form of academic support. Among valid responses, 84.6% rated ChatGPT as more useful than traditional resources such as office hours, peers, or tutors, and 80.1% agreed or strongly agreed that ChatGPT allows them to get help when they need it. Similarly, 84.1% agreed or strongly agreed that ChatGPT is easier to access than other academic support resources. These findings are important because they suggest that students value ChatGPT not only for its technical output but also for its availability. Open-ended responses reinforced this pattern, with students frequently describing ChatGPT as useful when office hours, teaching assistants, or peers were unavailable.

Student interaction patterns also suggest that many respondents describe their use of ChatGPT as iterative rather than purely answer-seeking. Among valid responses, 77.1% reported using ChatGPT to check their work, 76.0% reported asking follow-up questions, 62.9% reported requesting alternative explanations, and 36.0% reported refining prompts to improve answers. Only 17.1% selected "ask one question and use the answer." These results complicate a simplistic interpretation that students are merely copying outputs. Many students report using ChatGPT dialogically, as a tool for checking, clarifying, and refining their understanding.

Self-reported learning behaviors were also generally positive. Among valid responses, 89.7% agreed or strongly agreed that they ask ChatGPT follow-up questions to better understand concepts, 86.3% agreed or strongly agreed that they focus on understanding the solution rather than simply obtaining the answer, and 73.1% agreed or strongly agreed that ChatGPT helps them understand concepts more deeply. In addition, 86.4% reported critically evaluating ChatGPT's responses, and 72.7% reported verifying ChatGPT's answers using other resources such as notes or textbooks.

At the same time, the survey reveals meaningful tensions in students' reported experiences. Although most students report critical engagement and verification, 25.6% agreed or strongly agreed that they sometimes rely on ChatGPT without fully understanding the solution, while an additional 23.9% selected neutral on that item. Similarly, 39.2% agreed or strongly agreed that they sometimes struggle to determine whether ChatGPT's responses are correct, while 26.1% selected neutral. These results suggest that even in a sample where students report high levels of critical evaluation and verification, a substantial subset still experiences uncertainty about correctness or relies on AI-generated work without full understanding.

The survey also indicates that ChatGPT may influence help-seeking behavior and confidence. Among valid responses, 72.7% agreed or strongly agreed that ChatGPT makes it easier to ask questions they might not ask in class, and 51.1% agreed or strongly agreed that ChatGPT reduces hesitation to seek help compared to traditional classroom settings. In addition, 58.5% reported feeling more confident working through difficult material when using ChatGPT, and 48.0% reported that ChatGPT helps them stay engaged when stuck on a problem. However, only 18.2% agreed or strongly agreed that ChatGPT improved their sense of belonging in engineering courses, while 52.8% disagreed or strongly disagreed. These findings suggest that ChatGPT may reduce immediate barriers to help-seeking and support confidence, but it does not necessarily translate into a stronger sense of course belonging.

The survey also shows that students perceive ChatGPT as an accessible form of academic support. Among valid responses, 84.6% rated ChatGPT as more useful than traditional resources such as office hours, peers, or tutors, and 80.1% agreed or strongly agreed that ChatGPT allows them to get help when they need it. Similarly, 84.1% agreed or strongly agreed that ChatGPT is easier to access than other academic support resources. These findings are important because they suggest that students value ChatGPT not only for its technical output but also for its availability. Open-ended responses reinforced this pattern, with students frequently describing ChatGPT as useful when office hours, teaching assistants, or peers were unavailable. These patterns are consistent with recent work examining ChatGPT as a tool for inclusive academic support in engineering education, particularly in relation to access, immediacy of help, and reduced barriers to asking questions [14].

These results reveal a coherent pattern. ChatGPT is widely used and valued for access, immediacy, and conceptual support. Students often describe using it in reflective and iterative ways, including asking follow-up questions, checking work, and verifying answers. However, the data also show that self-reported engagement does not eliminate concerns about reliance, correctness, and the depth of understanding. These findings provide empirical support for the central claim of this paper: the primary challenge of AI in engineering education is not simply whether students use AI, but whether educational systems can still generate credible evidence of demonstrable competence when AI is embedded in the learning process.

7. Findings

The findings of this study are organized around the four research questions and reflect the integration of survey data, course-based observations, and the conceptual framework of demonstrable competence and engineering adequacy judgment. Across all findings, a consistent pattern emerges: ChatGPT expands access to academic support and supports task completion, but it also complicates how competence is demonstrated and evaluated.

7.1 RQ1: Patterns of AI Use in ECE Coursework

The data reveal that ChatGPT is not used sporadically or in isolated instances but is integrated into many students' problem-solving processes. Among students who responded to the frequency item, 90.8% reported at least some use of ChatGPT in a course context, and 72.3% reported using it occasionally or more frequently. While 40.5% reported weekly or daily use, the overall pattern indicates that ChatGPT has become a familiar academic support resource for many undergraduate students in ECE-related coursework.

The most common reported use was concept explanation, selected by 76.6% of respondents with valid task-use responses. This finding is important because it indicates that students often use ChatGPT not simply to obtain final answers, but to make course material more accessible. Coding/debugging was also common, reported by 58.1% of respondents, followed by studying for exams at 55.7% and homework problems at 41.3%. These patterns show that ChatGPT is used across conceptual, analytical, and implementation-oriented tasks, aligning with emerging engineering education research documenting generative AI use across programming, design, and learning-support contexts [6], [7]. The access-related findings also align with recent work examining ChatGPT as a tool for inclusive academic support in engineering education [14].

The interaction data further indicate that many students use ChatGPT iteratively. More than three-quarters of respondents reported using it to check their work, and a similar proportion reported asking follow-up questions. Nearly two-thirds reported requesting alternative explanations. These findings suggest that, for many students, ChatGPT functions as a responsive support system rather than merely an answer generator. At the same time, the availability of such immediate support may reorder the problem-solving process by making AI-assisted exploration an early step in learning rather than a later step used only after independent effort.

7.2 RQ2: Artifact Quality and Demonstrable Competence

The findings support a revised and more nuanced version of the artifact–competence divergence problem. The data do not show that students uniformly avoid reasoning or verification. In fact, many students report behaviors associated with active engagement: 89.7% ask follow-up questions, 86.3% focus on understanding rather than simply obtaining an answer, 86.4% critically evaluate responses, and 72.7% verify answers using other resources. These findings suggest that many students perceive themselves as using ChatGPT in ways that support learning.

However, the same dataset also reveals why self-reported engagement cannot be treated as equivalent to demonstrable competence. A quarter of respondents reported that they sometimes rely on ChatGPT without fully understanding the solution, and nearly two-fifths reported struggling to determine whether ChatGPT's responses are correct. These results indicate that even when students report critical engagement, some still experience uncertainty about correctness or rely on AI-generated explanations without full understanding. This pattern is consistent with prior research showing that AI-assisted environments can improve performance while obscuring reasoning processes and increasing the risk of overreliance or cognitive offloading [1], [3].

This pattern supports the central concern of the paper: the issue is not simply whether students use AI, nor whether they claim to verify AI-generated work. The deeper issue is whether their understanding can be demonstrated independently through explanation, adaptation, verification, and justification. In AI-enabled environments, self-reported effort and artifact quality are insufficient by themselves. Competence must be made visible through assessment practices that require students to show how they reason about and evaluate the work they produce.

7.3 RQ3: Assessment as the Determinant of Learning Visibility

The survey did not directly ask students to compare specific assessment formats such as oral exams, design reviews, or modified-parameter problems. Therefore, claims about assessment must be interpreted through the combined evidence of the survey, instructor observations, course artifacts, and the conceptual framework rather than through a single survey item.

The data nevertheless strongly support the need for assessment practices that make reasoning visible. Students report high levels of AI-supported access, explanation, checking, and verification, but also report uncertainty about correctness and occasional reliance without full understanding. This combination suggests that students' self-reported interaction with AI does not fully resolve the question of competence. Assessment is needed to determine whether students can explain, adapt, and justify AI-assisted work independently. This interpretation aligns with established engineering education research showing that active, reasoning-centered learning environments make student understanding more visible and support deeper engagement [8], [9].

In this sense, assessment remains the central mechanism for distinguishing between AI-supported learning and AI-supported artifact production. When assessments require students to explain their reasoning, modify solutions under changed conditions, validate results, or defend design decisions, they create evidence of competence that cannot be inferred from the artifact alone. When assessments rely primarily on final outputs, the visibility of competence is reduced.

7.4 RQ4: Implications for ABET-Aligned Competence

The findings suggest that existing ABET outcomes remain relevant in AI-enabled environments, but their interpretation must evolve. Outcomes related to problem solving, design, communication, and professional responsibility all assume that student work provides meaningful evidence of individual capability. When AI contributes to that work, this assumption must be re-examined [4].

Problem solving must be understood not simply as producing correct solutions, but as formulating problems, evaluating alternatives, and adapting solutions under changing conditions. Design must include justification of decisions in terms of constraints, tradeoffs, and uncertainty. Communication must involve explaining reasoning, not merely presenting results. Professional responsibility must include accountability for the validity and reliability of AI-assisted outputs. These shifts are consistent with broader engineering education goals that emphasize preparation for complex decision-making under uncertainty [5].

These shifts align directly with the concept of engineering adequacy judgment, which emphasizes the ability to determine when available evidence is sufficient to justify action. In educational terms, this means that students must demonstrate not only what they can produce, but whether they can evaluate the adequacy of what they produce in context.

7.5 Synthesis of Findings

The findings reveal a coherent and significant shift in engineering education. ChatGPT expands access to help, supports conceptual explanation, and enables students to continue working when they are stuck. At the same time, it complicates the relationship between artifact quality and demonstrable competence. Students frequently report using ChatGPT in reflective ways, but a substantial subset also reports uncertainty about correctness and reliance without full understanding.

This outcome is not inevitable. The survey suggests that many students want to use ChatGPT to understand, check, and refine their work. The educational challenge is therefore not to prevent AI use, but to design learning environments and assessments that require students to demonstrate the reasoning behind AI-supported outputs. These patterns provide the foundation for interpreting how AI reshapes the relationship between learning, performance, and assessment [1], [3].

8. Discussion

The findings of this study indicate that the integration of generative artificial intelligence into ECE education represents not simply a change in instructional tools, but a fundamental shift in how engineering knowledge is accessed, supported, evidenced, and evaluated in educational contexts. Students report using ChatGPT for concept explanations, coding/debugging, exam preparation, and homework support. They also report high levels of interaction with AI-generated outputs, including asking follow-up questions, checking work, requesting alternative explanations, critically evaluating responses, and verifying answers using other resources. These findings complicate simplistic narratives that frame student AI use primarily as avoidance, shortcutting, or academic misconduct [11], [12].

At the same time, the findings also reveal why AI-supported learning cannot be evaluated through artifact quality or self-report alone. Even in a dataset where students report high levels of critical engagement, a substantial minority acknowledge relying on ChatGPT without fully understanding the solution, and nearly two-fifths report difficulty determining whether ChatGPT's responses are correct. This pattern reflects a breakdown in the long-standing assumption that correct outputs provide reliable evidence of competence. It is also consistent with research showing that AI-assisted systems can support performance while obscuring the reasoning processes that assessment is intended to reveal [1], [3].

This breakdown, identified in this paper as the artifact–competence divergence problem, has implications that extend beyond classroom practice. It challenges the epistemic foundation on which engineering learning is evaluated. Historically, producing a correct solution required engagement with underlying principles, making the artifact itself a reasonable proxy for understanding. In AI-enabled environments, that proxy is no longer reliable. Students can arrive at correct answers through pathways that may include reasoning, scaffolding, verification, partial understanding, or uncritical acceptance. The artifact alone cannot distinguish among these pathways.

Importantly, this divergence does not imply that learning has diminished or disappeared. Rather, it suggests that learning has become less observable through traditional measures. Students may still be developing understanding, and the survey data indicate that many actively use ChatGPT to ask questions, clarify concepts, and check work. However, the connection between that understanding and their submitted work has become less direct and less transparent. This reduced visibility is consistent with patterns of automation bias and cognitive offloading, in which interaction with AI systems can substitute for internal reasoning while maintaining the appearance of engagement [3].

The findings further demonstrate that this outcome is not an inherent property of AI but is shaped by the structure of assessment. Assessment design, not the presence of AI, is the decisive factor in determining whether AI functions as a learning support or a substitute for understanding. When evaluation requires students to explain reasoning, adapt solutions under modified conditions, verify results, and justify decisions, the processes that define engineering competence remain visible. In these contexts, AI can act as a scaffold that supports deeper engagement. In contrast, when assessment focuses primarily on final artifacts, AI can enable correct outputs without requiring demonstrable competence, thereby obscuring underlying gaps in understanding. This interpretation is consistent with research showing that active and reasoning-centered educational practices strengthen conceptual engagement and make learning processes more visible [8], [9].

From this perspective, assessment is not simply a mechanism for measuring learning outcomes; it is the mechanism that defines what counts as evidence of learning. It determines which behaviors are required, which processes are visible, and how competence is inferred. In AI-enabled environments, this role becomes even more critical because artifacts alone no longer provide sufficient information about student understanding.

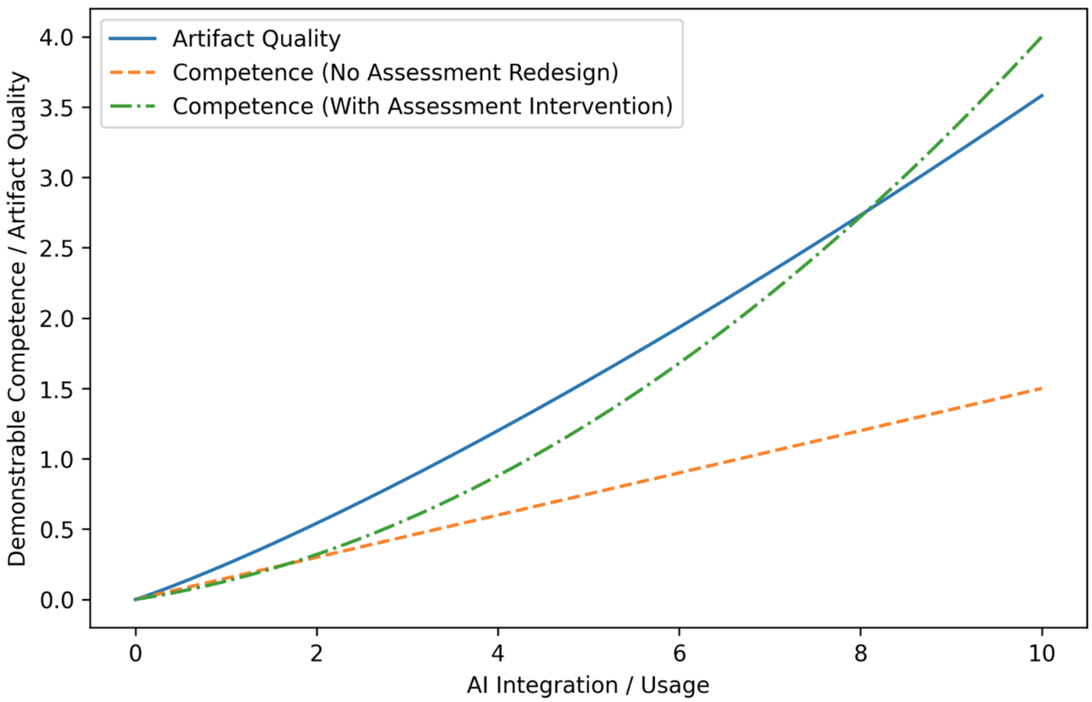

Figure 1. Conceptual model of artifact–competence divergence in AI-enabled engineering education. As AI integration increases, artifact quality (performance) improves steadily, while demonstrable competence may lag under artifact-based assessment conditions. When assessment is redesigned to emphasize explanation, adaptation, and justification, competence more closely aligns with performance.

Figure 1 provides a conceptual representation of this relationship. As illustrated, artifact quality tends to increase with AI integration, while demonstrable competence may remain partially decoupled under artifact-based assessment conditions. When assessment is redesigned to emphasize explanation, adaptation, and justification, competence more closely aligns with performance. The figure therefore highlights that the central issue is not AI itself, but whether assessment practices preserve the visibility of the reasoning processes that define engineering competence. This framing positions AI integration as an evidentiary validity problem, in which the key question is no longer whether students can produce correct outputs, but whether those outputs can still serve as credible evidence of competence. In this sense, the challenge introduced by AI is not technological but epistemic: it requires redefining what counts as sufficient evidence of engineering competence.

The implications of this shift become particularly clear when considered in relation to engineering practice. A circuit that appears correct under nominal conditions may fail when parameters change or when non-ideal effects are introduced. Code that executes successfully may still contain latent faults that emerge under different timing conditions or hardware constraints. A design that appears functional may not meet reliability or safety requirements when deployed in real environments. In each of these cases, the critical issue is not correctness in isolation, but whether the available evidence is sufficient to justify action. These examples underscore that correctness in isolation has never been sufficient in engineering practice, and AI makes this long-standing reality unavoidable in educational contexts [5].

The findings also clarify the relationship between AI use and overreliance. Rather than viewing overreliance as a simple behavioral issue, it can be understood as a consequence of misaligned evidentiary structures. When assessment does not require verification or explanation, reliance on AI may become rational from the student's perspective, as it maximizes efficiency without affecting evaluation outcomes. Conversely, when assessment requires demonstration of reasoning, reliance without understanding becomes insufficient. This interpretation aligns with research on human–AI interaction, which emphasizes that reliance is shaped by task structure and evaluation conditions rather than by user intent alone [3].

These insights position the artifact–competence divergence problem as a central issue for engineering education in the age of AI. It is not a peripheral concern, but a structural consequence of how generative systems interact with existing pedagogical and assessment practices. Addressing this problem therefore requires not limiting AI use but redesigning the evidentiary structures through which engineering competence is made visible.

This paper contributes to that effort by introducing an assessment-centered framework grounded in engineering adequacy judgment, which emphasizes the ability to determine when evidence is sufficient to justify action. This framework provides a foundation for preserving the core intellectual and professional goals of engineering education in AI-enabled environments by shifting the focus from outputs to judgment.

9. Implications for Engineering Education

The findings of this study have significant implications for how engineering education must evolve in response to generative AI. Most importantly, they indicate that the central challenge is not whether AI should be permitted or restricted, but whether educational systems can continue to produce credible evidence of competence when artifacts are no longer reliable indicators of understanding. Addressing this challenge requires a reorientation of assessment, instruction, and program-level evaluation toward the preservation of demonstrable engineering judgment.

A primary implication is that verification must be treated as an explicit and assessable learning outcome, rather than an implicit expectation embedded within problem-solving tasks. In traditional ECE instruction, verification is often assumed to occur as part of the solution process but is not always directly evaluated. In AI-enabled environments, this assumption is no longer sufficient. Students must be required to demonstrate how they evaluate the correctness and reliability of their results, particularly when those results are generated with external assistance.

This includes not only confirming numerical accuracy, but also examining underlying assumptions, testing robustness under varying conditions, and identifying potential sources of error. Without such expectations, students may complete tasks successfully while bypassing the verification processes that define engineering competence. This shift is consistent with broader research emphasizing that learning outcomes depend on the extent to which reasoning and evaluation processes are made visible through assessment [8], [9].

A second implication is that assessment must make uncertainty explicit and evaluable. Engineering problems rarely exist under perfectly defined conditions, and competent engineers must be able to reason about incomplete information. In educational contexts, however, assignments are often structured to minimize ambiguity, presenting well-defined problems with clear answers. Generative AI reinforces this tendency by producing solutions that appear complete and authoritative. To counteract this effect, assessments should require students to identify what is known, what remains uncertain, and how that uncertainty affects the reliability of their solutions. This may involve asking students to justify assumptions, discuss limitations, or propose additional analyses required to validate their results. By doing so, assessment shifts from evaluating correctness to evaluating judgment under uncertainty, which more closely reflects engineering practice [5].

A third implication is that instructional design must separate the generation of solutions from the authorization of their use. Generative AI systems are highly effective at producing candidate solutions, and their use in this capacity is likely to continue. However, the educational objective cannot end with solution generation. Students must also demonstrate the ability to determine whether those solutions are appropriate for use in a given context. This requires tasks that explicitly distinguish between producing an answer and deciding whether that answer is sufficient to support further action. For example, students may be asked to evaluate AI-generated outputs, identify potential limitations, adapt solutions under modified conditions, or defend their reasoning in real time. Such tasks ensure that AI functions as a tool within the learning process rather than as a substitute for it.

A fourth implication concerns the interpretation of ABET-aligned learning outcomes. The findings suggest that these outcomes remain valid, but their use must evolve to reflect AI-enabled contexts. Problem solving must be understood not as the ability to produce correct solutions, but as the ability to formulate problems, evaluate alternatives, and adapt solutions under changing conditions. Design must include justification of decisions in terms of constraints, tradeoffs, and uncertainty. Communication must extend beyond presenting results to explaining the reasoning and assumptions that underlie those results. Professional responsibility must include accountability for the validity and reliability of AI-assisted work. These interpretations align with the broader goal of engineering education to prepare students for decision-making under uncertainty, rather than for the production of isolated correct answers [4], [5].

At the program level, these findings highlight the need for systematic attention to evidentiary validity within continuous improvement processes. If student artifacts become increasingly polished due to AI assistance while explanatory and verification skills remain underdeveloped, traditional assessment data may provide a misleading picture of learning outcomes. Programs must therefore evaluate not only what students produce, but how they demonstrate understanding. This may involve incorporating new forms of assessment, such as oral examinations, design reviews, live problem-solving tasks, or process-based evaluation methods that capture reasoning and decision-making. Such approaches are consistent with research in engineering education emphasizing the importance of making learning processes observable rather than inferring understanding from final outputs alone [8], [9].

Finally, these findings underscore the importance of explicitly teaching engineering judgment as a core competency. Students should not be expected to develop adequacy judgment implicitly through repeated exposure to problem-solving tasks. Instead, instruction should include guidance on how to evaluate evidence, recognize uncertainty, and determine when additional validation is required. This includes incorporating examples from real-world engineering practice where correct-looking solutions fail due to unexamined assumptions or insufficient verification. By making these processes explicit, educators can help students develop the capacity to assess not only whether a solution is correct, but whether it is sufficiently reliable for use.

These implications suggest that the appropriate response to generative AI is not restriction, but reconstruction of the evidentiary structures that support learning. Engineering education can integrate generative AI systems while preserving its core intellectual and professional goals by aligning assessment and instruction with the behaviors that define engineering competence: verification, explanation, adaptation, and adequacy judgment.

10. Conclusion

The integration of generative AI6 into electrical and computer engineering education represents a fundamental shift in how learning is accessed, supported, produced, observed, and evaluated. This paper has argued that the most significant consequence of this shift is not the presence of AI itself, but the disruption it introduces to the evidentiary foundations of engineering education. When students can generate correct or useful outputs with AI support, the long-standing assumption that artifact correctness reflects competence no longer holds on its own.

The findings of this study make this disruption visible in a nuanced way. Students report using ChatGPT widely for concept explanations, coding/debugging, studying, and homework support. They also report high levels of follow-up questioning, critical evaluation, work checking, and verification using other resources. These findings suggest that many students are not simply using AI passively; they are using it as an interactive academic support system. However, the same dataset also shows that a meaningful subset of students sometimes rely on ChatGPT without fully understanding the solution or struggle to determine whether its responses are correct. This misalignment between AI-supported access, artifact production, self-reported engagement, and demonstrable competence reveals that correctness alone is no longer a sufficient indicator of understanding [1], [3].

Addressing this challenge requires more than incremental adjustments to instructional practice. It requires a fundamental shift in how engineering education defines and evaluates learning. This paper has argued that competence must be understood not as the ability to produce correct answers, but as the ability to determine when available evidence is sufficient to justify action under uncertainty. This reframing aligns with the realities of engineering practice, where decisions are made not on the basis of complete knowledge, but through disciplined judgment about sufficiency, reliability, and risk [5].

Within this perspective, assessment emerges as the central mechanism through which competence is preserved. When evaluation requires students to explain reasoning, adapt solutions, verify results, and justify decisions, the processes that define engineering judgment remain visible even in the presence of AI. When evaluation relies primarily on final artifacts, those processes can be bypassed, allowing AI to substitute for understanding. The distinction is not merely pedagogical; it determines whether engineering education continues to produce graduates capable of responsible decision-making.

This shift carries implications beyond individual courses. It requires a re-examination of how programs interpret accreditation outcomes, how evidence of learning is collected, and how students are prepared for professional practice. In particular, it highlights the need to explicitly develop engineering adequacy judgment, the ability to determine when a solution is sufficiently validated to support action. This capability has always been central to engineering, but in AI-enabled environments it can no longer be assumed to emerge implicitly through problem solving.

The challenge facing engineering education is not whether students can use AI effectively, but whether they can continue to exercise engineering judgment in AI-augmented environments. In a context where correct answers can be produced with minimal effort, correctness is no longer epistemically sufficient. What matters instead is whether students can justify, verify, and responsibly act on those solutions.

Engineering education must therefore shift from evaluating what students produce to evaluating whether they know when they have enough evidence to act. Without this shift, there is a risk that students will learn to generate solutions without learning how to trust them. This paper offers a path forward, one that integrates technological capability with the enduring requirements of responsible engineering practice. By reframing AI integration as an evidentiary validity problem and emphasizing the role of adequacy judgment in engineering competence, it clarifies how learning can remain both visible and meaningful in AI-enabled environments.

In this sense, AI does not reduce the need for engineering judgment; it makes its absence more difficult to detect.

References

[1] Z. Swiecki, H. Khosravi, G. Chen, R. Martinez-Maldonado, J. M. Lodge, S. Milligan, N. Selwyn, and D. Gašević, “Assessment in the age of artificial intelligence,” *Computers and Education: Artificial Intelligence*, vol. 3, p. 100075, 2022. doi: 10.1016/j.caeai.2022.100075

[2] E. Kasneci et al., “ChatGPT for good? On opportunities and challenges of large language models for education,” *Learning and Individual Differences*, vol. 103, p. 102274, 2023. doi: 10.1016/j.lindif.2023.102274

[3] Z. Buçinca, M. B. Malaya, and K. Z. Gajos, “To trust or to think: Cognitive forcing functions can reduce overreliance on AI,” *Proc. ACM Hum.-Comput. Interact.*, vol. 5, no. CSCW1, 2021. doi: 10.1145/3449287

[4] ABET Engineering Accreditation Commission, *Criteria for Accrediting Engineering Programs*, 2024–2025. [Online]. Available: https://www.abet.org

[5] National Academy of Engineering, *Educating the Engineer of 2020: Adapting Engineering Education to the New Century*, Washington, DC: National Academies Press, 2005. doi: 10.17226/11338

[6] M. J. Prince, “Does active learning work? A review of the research,” *Journal of Engineering Education*, vol. 93, no. 3, pp. 223–231, 2004. doi: 10.1002/j.2168-9830.2004.tb00809.x

[7] S. Freeman et al., “Active learning increases student performance in STEM,” *PNAS*, vol. 111, no. 23, pp. 8410–8415, 2014. doi: 10.1073/pnas.1319030111

[8] A. Johri, B. M. Olds, and K. O’Connor, “Situative frameworks for engineering learning: Implications for engineering education research,” *IEEE Trans. Educ.*, vol. 57, no. 4, pp. 210–215, 2014. doi: 10.1109/TE.2014.2313297

[9] S. R. Brunhaver, R. S. Sheppard, and K. Chen, “Longitudinal study of engineering student pathways and professional formation,” *IEEE Trans. Educ.*, vol. 63, no. 3, pp. 213–221, 2020. doi: 10.1109/TE.2020.2972444

[10] M. L. Loughry, J. W. Ohland, and D. J. Woehr, “Assessing teamwork skills in engineering education,” *IEEE Trans. Educ.*, vol. 57, no. 4, pp. 238–245, 2014. doi: 10.1109/TE.2014.2313284

[11] D. Cotton, P. Cotton, and J. Shipway, “Chatting and cheating: Ensuring academic integrity in the era of ChatGPT,” *Innovations in Education and Teaching International*, 2023. doi: 10.1080/14703297.2023.2190148

[12] S. Rudolph, S. Tan, and S. Tan, “ChatGPT: Bullshit spewer or the end of traditional assessments in higher education?” *Journal of Applied Learning and Teaching*, vol. 6, no. 1, 2023.

[13] J. Baidoo-Anu and L. Owusu Ansah, “Education in the era of generative AI: Uses, benefits, and limitations of ChatGPT,” *SSRN*, 2023. doi: 10.2139/ssrn.4337484

[14] M. El Helbawy and S. Sierra, “Exploring ChatGPT as a tool for inclusive academic support in engineering education,” in *Proc. 2026 ASEE Zone IV Conf.*, Pomona, CA, USA, 2026.