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# Integrating AI Tools into Electrical and Computer Engineering Courses for Student Learning and Industry Readiness

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# Integrating AI Tools into Electrical and Computer Engineering Courses for Student Learning and Industry Readiness

**Abstract**

Artificial intelligence (AI) tools such as ChatGPT and GitHub Copilot have quickly entered higher education, raising both opportunities and questions for engineering educators. While essay-based disciplines are facing immediate disruption, traditional engineering courses remain less directly affected, since examinations still rely heavily on analytical skills. However, in professional engineering practice, AI tools are already widely used in programming, design, and system analysis. This contrast highlights the need for educators to introduce students to AI tools early-framing them as resources to be used ethically, critically, and proficiently.

This paper describes ongoing efforts within the Electrical and Computer Engineering Department at California Baptist University to integrate AI into traditional courses such as Circuit Theory, Digital Logic, Electronics, and Power Electronics. These efforts span multiple courses at different curricular levels and are guided by a common instructional framework that emphasizes verification, engineering judgment, and ethical responsibility. The objective is to prepare students to recognize that AI outputs are not infallible, to use course knowledge to verify and refine results, and to develop professional habits of ethical tool use.

Assignments are designed to pair traditional problem-solving with AI-supported attempts. Students solve problems both with and without AI, then compare results, identify errors, and reflect on differences in clarity and accuracy. Grading rubrics emphasize not only technical correctness but also the quality of prompts, the ability to critique and improve AI-generated work, and the clarity of written explanations. Across courses, pre- and post-assignment surveys and qualitative student artifacts provide insight into how these experiences shape students' confidence, verification habits, and ethical awareness when using AI tools.

Results suggest that structured exposure to AI encourages engagement, strengthens critical thinking, and helps students build confidence in applying engineering judgment. Survey results across multiple courses suggest increased confidence in using AI tools alongside sustained or recalibrated emphasis on verification and ethical responsibility. By positioning AI as a supplement rather than a shortcut, this approach reinforces foundational skills while equipping students for an industry environment where AI is increasingly standard.

**Index Terms-** Artificial intelligence in engineering education, instructional innovation, electrical and computer engineering, circuit theory, digital logic, electronics, power electronics, pedagogy, ethical use of AI, critical thinking, industry readiness.

## I. Introduction

Artificial intelligence (AI) tools based on large language models and machine learning have rapidly entered higher education, changing how students access information, generate content, and approach problem solving. Tools such as ChatGPT and GitHub Copilot are now widely available and increasingly used by students across disciplines. Their emergence has prompted extensive discussion among educators regarding academic integrity, learning outcomes, and the appropriate role of AI in coursework [1]-[3].

Much of the early impact of generative AI has been observed in essay-based disciplines, where AI systems can produce complete written responses with minimal human input [2], [3]. In contrast, traditional Electrical and Computer Engineering (ECE) courses remain less directly affected. Core assessments such as midterm and final examinations continue to rely heavily on analytical reasoning, mathematical formulation, and structured problem solving-skills that are difficult to replace with AI tools in supervised settings. As a result, some engineering programs have been slower to formally address AI use within their curricula.

Despite this relative insulation, AI tools are already deeply embedded in professional engineering practice. AI-assisted environments are widely used in software development, system design, debugging, and documentation [4], [5]. Engineers in industry increasingly interact with AI-enabled tools as part of everyday workflows, whether for exploring design alternatives, accelerating development, or supporting decision-making. Graduates entering the workforce are therefore expected not only to possess strong technical foundations but also to use AI tools efficiently, responsibly, and critically.

This discrepancy between academic assessment practices and professional engineering workflows highlights a growing gap in engineering education. Ignoring AI use entirely may leave students underprepared for industry realities, while unstructured or unguided use risks encouraging over-reliance, superficial understanding, or diminished verification habits. Prior work in human–automation interaction has shown that over-reliance on automated systems can introduce automation bias, reducing users' tendency to critically evaluate outputs [6]. These concerns are particularly relevant in ECE, where incorrect assumptions or unverified results can have significant technical and societal consequences.

In response to these challenges, the Electrical and Computer Engineering Department at California Baptist University adopted a deliberate approach to AI integration. Rather than banning AI tools or allowing unrestricted use, AI was intentionally incorporated into existing coursework in a structured manner. Across multiple courses and curricular levels, students were required to engage in traditional problem-solving, generate AI-assisted solutions, verify results using analytical reasoning, simulation, or hardware demonstration, and reflect on ethical and professional responsibility. This approach aligns with prior findings in engineering education that technology integration is most effective when it is intentional, aligned with learning objectives, and supported by appropriate scaffolding [7].

This paper presents a multi-course, evidence-based examination of that approach, drawing on implementations in Circuit Theory I, Digital Logic Design, Electronics I, and Power Electronics. By examining student perceptions, verification behaviors, and ethical awareness across these courses, this work seeks to contribute practical guidance for ECE educators navigating the integration of AI tools while maintaining rigor and professional standards.

## II. Motivation and Background

Engineering education has long emphasized analytical reasoning, verification, and sound engineering judgment as core competencies. These skills are central to professional practice, particularly in electrical and computer engineering (ECE), where design errors or unverified assumptions can lead to system failure, safety risks, or significant economic consequences. As a result, ECE curricula have traditionally prioritized manual analysis, structured problem solving, and independent verification as foundational learning outcomes.

The increasing availability of generative AI tools challenges this instructional paradigm. While AI systems can generate explanations, code, and design suggestions rapidly, their outputs may contain incorrect assumptions, incomplete reasoning, or context-insensitive errors. Prior work in engineering education has raised concerns that unstructured AI use may reduce conceptual engagement or encourage over-reliance on automated outputs if verification is not explicitly required [8], [9]. These concerns are particularly relevant in ECE, where correctness is often binary and errors may not be immediately apparent without careful analysis or simulation.

At the same time, professional engineering practice is rapidly evolving. Studies reported in IEEE venues indicate that AI-assisted tools are already being incorporated into software development, system modeling, and design exploration workflows [10], [11]. Rather than replacing engineers, these tools increasingly function as productivity aids and exploratory assistants, shifting the engineer's role toward evaluation, integration, and judgment. Graduates entering industry are therefore expected not only to understand core technical principles but also to interact effectively with AI-enabled tools while remaining accountable for final outcomes.

ASEE research on instructional innovation consistently emphasizes that new technologies are most effective when integration is intentional and aligned with learning objectives, rather than additive or reactive [7]. Within the context of AI, recent ASEE studies have suggested that students benefit most when AI tools are framed as supports for exploration and explanation, provided that assignments require independent reasoning, justification, and verification [2], [12]. These findings motivate an instructional approach that neither bans AI outright nor allows unrestricted use, but instead embeds AI within structured activities that reinforce traditional engineering competencies.

Ethical considerations further strengthen the motivation for guided AI integration. IEEE and ASEE publications have highlighted the importance of preparing engineering students to engage emerging technologies responsibly, emphasizing transparency, accountability, and professional integrity [13], [14]. When AI-generated outputs are used without verification or attribution, these principles may be compromised. Introducing ethical reflection within technical coursework helps students recognize that responsible AI use is not merely a compliance issue but a core element of professional engineering practice.

Taken together, prior work suggests that the key challenge for ECE educators is not whether AI tools should be acknowledged, but how they can be integrated in ways that preserve rigor while preparing students for AI-enabled professional environments. This paper builds on that body of work by examining a multi-course, evidence-based implementation in which AI use is explicitly paired with verification, documentation, and ethical reflection. By situating AI within existing coursework and emphasizing engineering judgment over automation, the approach described here seeks to align educational practice with both professional expectations and established principles of effective engineering pedagogy.

## III. Instructional Context and Pedagogical Framework

The instructional approach described in this paper was developed within the Electrical and Computer Engineering (ECE) curriculum at California Baptist University and implemented across multiple required courses at different curricular levels. Rather than introducing AI-related content as standalone modules, AI integration was embedded within existing assignments and laboratories to preserve course learning objectives while exposing students to emerging tools in authentic engineering contexts. This approach aligns with prior ASEE findings that curricular innovations are most effective when they are integrated into core coursework rather than treated as add-ons [15].

Across all courses examined in this study, AI integration followed a common pedagogical framework centered on verification, engineering judgment, and ethical responsibility. The framework was designed to ensure that AI tools functioned as learning supports rather than solution authorities and that students remained accountable for correctness and decision-making. While the specific assignments differed by course content and level, each implementation adhered to the same set of guiding principles.

First, **AI was explicitly framed as a hypothesis generator rather than an authoritative source**. Students were encouraged to use AI tools to explore solution approaches, generate explanations, or draft initial designs, but were instructed that AI outputs should be treated as candidate solutions requiring evaluation. This framing is consistent with ASEE and IEEE literature emphasizing the importance of maintaining human judgment and critical evaluation when interacting with automated systems [16], [17].

Second, **verification was required as an explicit deliverable**. Depending on the course context, verification took the form of analytical derivations, circuit simulation, timing analysis, or hardware demonstration. Students were required to verify both manually derived and AI-assisted solutions using the same criteria, reinforcing the principle that correctness must be established independently of the tool used to generate a result. Prior ASEE studies have shown that requiring explicit verification artifacts promotes deeper conceptual understanding and discourages superficial solution adoption [18].

Third, **transparency and documentation of AI use were emphasized**. In courses where AI use was permitted, students were required to disclose tool usage, document prompts and outputs, and describe how AI-generated content was modified or verified. This requirement was intended to promote ethical practice, accountability, and reflective learning, and is consistent with IEEE and ASEE recommendations for responsible use of emerging technologies in engineering education [19], [20].

Finally, **ethical reflection was integrated into technical assignments rather than treated as a separate topic**. Students were asked to consider the professional implications of relying on AI-generated outputs, including the risks of unverified assumptions and the engineer's responsibility for final decisions. Embedding ethical reflection within technical work reflects ASEE guidance that ethics education is most effective when situated in discipline-specific contexts [21].

Importantly, this framework was applied across multiple courses spanning sophomore- to senior-level content, allowing examination of how students at different stages of the curriculum respond to intentional AI integration. By maintaining a consistent pedagogical approach while varying technical context, the implementations described in this paper provide insight into how AI-related instructional strategies can be scaled across an ECE program without compromising rigor or coherence.

## IV. Course Implementations and Evidence

### A. EGR231: Circuit Theory I

#### 1. Course Context

Circuit Theory I (EGR231) is a sophomore-level engineering course required for multiple engineering majors, including Electrical and Computer Engineering(ECE), Mechanical Engineering(ME), and Biomedical Engineering(BME). During the term examined in this study, the course enrolled 97 students representing three engineering majors, with approximately 74% Mechanical Engineering students and 15% Electrical and Computer Engineering students. The course focuses on foundational circuit analysis techniques such as Ohm's law, Kirchhoff's laws, nodal analysis, and mesh analysis, and serves as a gateway course for subsequent ECE and ME coursework.

Because EGR231 emphasizes analytical problem solving and mathematical formulation, it provides an appropriate context for introducing AI tools in a controlled manner. Prior ASEE studies have identified gateway circuit courses as particularly sensitive to instructional changes, as they play a critical role in shaping students' problem-solving habits and conceptual foundations [22]. For this reason, AI integration in EGR231 was intentionally limited in scope and positioned as a supplement to, rather than a replacement for, traditional analytical methods.

#### 2. Assignment Design and Implementation

An AI-integrated assignment was introduced during the final week of the semester, after students had completed instruction and practice in nodal analysis. The assignment required students to solve a multi-node resistive circuit problem using traditional hand analysis and then to generate a solution using a generative AI tool of their choice. Students were instructed to compare the two solutions, identify any discrepancies, and reflect on differences in approach, clarity, and correctness.

To reinforce verification and accountability, students were required to submit handwritten analytical work alongside AI-generated outputs. Written reflections emphasized the importance of validating AI-generated results using circuit laws and independent reasoning. This design aligns with ASEE recommendations that emerging technologies be introduced in ways that reinforce, rather than bypass, core learning objectives in foundational engineering courses [23].

**3. Survey Methodology**

To assess student perceptions related to AI use, pre- and post-assignment surveys were administered anonymously using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Survey items measured three constructs: confidence in using AI tools for engineering problem-solving (AI confidence), perceived ability to verify and evaluate AI-generated results (verification skill), and awareness of ethical and responsible AI use in engineering practice (ethical awareness).

A total of 70 students completed the pre-survey, and 52 students completed the post-survey. While the response rates differed between the two surveys, this approach is consistent with prior ASEE classroom-based studies that rely on voluntary student participation [24].

**4. Survey Results**

Table 1 summarizes the pre- and post-assignment survey results for EGR231.

**Table 1. Pre/Post Survey Results for EGR231 Circuit Theory I**

| Dimension | Pre Mean | Post Mean | Δ Change | Interpretation |
|---|---|---|---|---|
| AI Confidence | 3.09 | 3.62 | +0.53 | Moderate increase in confidence using AI tools |
| Verification Skill | 4.09 | 4.30 | +0.21 | Reinforcement of checking and validation behaviors |
| Ethical Awareness | 4.59 | 4.26 | −0.33 | High baseline; slight recalibration after hands-on exposure |

Results indicate that students' confidence in using AI tools increased following structured exposure, while confidence in verification remained high. The slight decrease in ethical awareness may reflect a recalibration effect rather than diminished ethical understanding. However, given the voluntary response rates and moderate sample size, this interpretation should be treated as exploratory. Post-survey means remained above 4.0, suggesting sustained emphasis on ethical responsibility.

**5. Observations and Student Reflections**

Open-ended student reflections revealed that many students found AI-generated explanations helpful for reviewing concepts but expressed skepticism regarding numerical accuracy and intermediate reasoning steps. Several students reported identifying errors in AI-generated nodal equations or solution steps, reinforcing the importance of independent verification. These observations are consistent with prior ASEE findings that students benefit most from AI tools when verification is explicitly required [2].

Overall, the EGR231 implementation demonstrates that AI tools can be introduced in a foundational circuit analysis course without undermining analytical rigor, provided that assignments emphasize verification, reflection, and accountability.

### B. EGR234: Digital Logic Design (Qualitative Case Study)

#### 1. Course Context

Digital Logic Design (EGR234) is an undergraduate course that introduces students to combinational and sequential logic design using hardware description languages (HDLs), simulation-based verification, and FPGA implementation. The course emphasizes correctness, timing behavior, and systematic verification, making it a natural environment for examining AI-assisted design within a controlled, artifact-driven context.

Unlike analytically focused circuit courses, digital logic design allows correctness to be evaluated through simulation waveforms and hardware behavior. Prior ASEE work has identified digital design laboratories as particularly effective settings for reinforcing verification habits, as design correctness can be objectively demonstrated and tested [25]. This characteristic makes EGR234 well suited for examining how students interact with AI-generated design suggestions while remaining accountable for final implementation.

#### 2. Assignment Design and AI Integration

The AI-integrated activity was implemented in **Lab 8: Basic Memory Elements**, which required students to design and implement a gated D latch and a master-slave D flip-flop. Students were required to use dataflow modeling and hierarchical design techniques, and to verify their designs through multiple stages, including behavioral simulation, post-implementation timing simulation, and hardware demonstration on an FPGA development board.

AI tool use was permitted but constrained. Students were explicitly informed that AI-generated HDL code should not be treated as authoritative and that all designs would be evaluated based on simulation results and observed hardware behavior. To promote transparency and accountability, students who used AI tools were required to complete an AI Assistance Log, documenting the tools used, the nature of the prompts, and how AI-generated outputs were modified or verified. This requirement aligns with ASEE recommendations that emerging technologies be accompanied by explicit documentation and reflection requirements [26].

#### 3. Artifact-Based Evaluation Methodology

Because survey response rates were limited in this course, EGR234 was treated as a qualitative case study rather than a quantitative analysis. Evaluation focused on student artifacts, including HDL source files, simulation waveforms, timing reports, and hardware demonstration results. Four student teams were selected for closer examination, representing a range of AI usage patterns.

Three teams reported direct use of generative AI tools, while one team used AI-generated examples only for comparison and confirmation. Artifact review focused on how students validated AI-assisted designs, responded to errors, and adhered to modeling constraints. This artifact-based approach is consistent with ASEE qualitative research methods commonly used in laboratory-based engineering education studies [27].

**4. Observations and Findings**

Analysis of student artifacts revealed that AI tools were primarily used for scaffolding and code structuring, rather than as a substitute for verification. In multiple cases, students identified errors or omissions in AI-generated HDL code, particularly related to sensitivity lists, clocking behavior, or board-specific constraints. These errors were typically detected through simulation mismatches or failed hardware demonstrations, reinforcing the role of verification as a central learning outcome.

A recurring observation was that AI tools were least effective in addressing context-specific implementation details, such as FPGA pin assignments and timing constraints. Students reported spending additional time debugging AI-generated suggestions in these areas, which ultimately reinforced the importance of understanding toolchains and hardware context. Similar limitations of AI-assisted design in hardware-centric tasks have been reported in IEEE education-focused publications [28].

**5. Instructional Implications**

The EGR234 implementation demonstrates that AI tools can be incorporated into digital logic laboratories without undermining verification-focused learning outcomes when assignments enforce modeling constraints, require simulation and hardware evidence, and emphasize transparency of tool use. By positioning AI as a supportive but fallible resource, the lab encouraged students to engage critically with AI-generated outputs and to rely on simulation and hardware behavior as the ultimate indicators of correctness.

This qualitative case study complements the survey-based findings in other courses by illustrating how structured constraints and artifact-based verification shape responsible AI use in a design-oriented ECE context.

**C. EGR333: Electronics I**

**1. Course Context**

Electronics I (EGR333) is an upper-division undergraduate course focused on analog electronics, including semiconductor device operation, biasing techniques, small-signal modeling, and amplifier design. The course emphasizes the integration of analytical derivations with circuit simulation to validate performance metrics such as gain, operating point stability, and signal swing. As such, EGR333 provides a design-oriented context in which verification through simulation is a routine and expected component of student work.

Prior ASEE research has noted that upper-division electronics courses are well suited for examining students' transition from purely analytical problem solving to design verification workflows that resemble professional practice [29]. This makes EGR333 an appropriate setting for investigating how students interact with AI-generated design suggestions while remaining responsible for validating performance and meeting specifications.

**2. Assignment Design and AI Integration**

The AI-integrated activity was implemented as a homework assignment focused on the design of a single-stage common-emitter BJT amplifier. Students were instructed to complete the design using traditional analytical methods, including DC bias analysis and small-signal modeling, and then to generate an AI-assisted design using a generative AI tool of their choice. Both designs were subsequently implemented and evaluated using circuit simulation.

Students were required to compare manual and AI-assisted designs, identify discrepancies in assumptions or calculated component values, and reflect on the extent to which AI-generated solutions satisfied design specifications. AI use was explicitly permitted but framed as a support tool rather than an authoritative source. This structure aligns with ASEE guidance recommending that AI integration in design-oriented courses emphasize comparison, critique, and verification rather than substitution [30].

**3. Survey Methodology**

To assess student perceptions related to AI use in a design context, pre- and post-assignment surveys were administered using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Survey items measured the same three constructs used in other courses: AI confidence, verification skill, and ethical awareness. This consistency allowed comparison across course levels while accounting for differences in technical context.

Twenty-two students completed the pre-survey, and seventeen students completed the post-survey. While the sample size was modest, it is consistent with ASEE studies conducted in upper-division courses with smaller enrollments [31].

**4. Survey Results**

Table 2 summarizes the pre- and post-assignment survey results for EGR333.

**Table 2. Pre/Post Survey Results for EGR333 Electronics I**

| Dimension | Pre Mean | Post Mean | Δ Change | Interpretation |
|---|---|---|---|---|
| AI Confidence | 3.50 | 4.42 | +0.92 | Substantial increase following structured design exposure |
| Verification Skill | 4.43 | 4.14 | −0.29 | Calibration effect after encountering AI-generated design errors |

| Dimension | Pre Mean | Post Mean | Δ Change | Interpretation |
| --- | --- | --- | --- | --- |
| Ethical Awareness | 4.50 | 4.50 | 0.00 | Ethical awareness remained consistently high |

Results indicate a notable increase in student confidence using AI tools in a design-oriented context. At the same time, verification confidence decreased slightly while remaining high in absolute terms, which may indicate a recalibration of confidence as students encountered limitations or errors in AI-generated designs. Given the modest sample size in this upper-division course, firm conclusions regarding changes in verification skill cannot be drawn.

**5. Observations and Student Reflections**

Student reflections revealed that AI-generated amplifier designs often appeared reasonable at first glance but failed to meet specifications without further modification. Common issues included incorrect biasing assumptions, omission of loading effects, or insufficient attention to design constraints. Students frequently reported that simulation results differed from AI-predicted performance, prompting further analysis and adjustment.

These observations reinforce the role of verification as a central learning outcome in EGR333. Similar findings have been reported in ASEE and IEEE literature, which note that AI tools can accelerate design exploration but require careful evaluation to avoid propagation of subtle errors [32].

Overall, the EGR333 implementation demonstrates that AI integration in an upper-division electronics course can enhance student engagement and confidence while simultaneously strengthening awareness of the need for independent verification and professional judgment.

**D. EGR433: Power Electronics**

**1. Course Context**

Power Electronics (EGR433) is a senior-level undergraduate course focusing on the analysis and design of switching power converters. Topics include DC-DC converter topologies, steady-state and small-signal modeling, efficiency considerations, and practical implementation issues. The course emphasizes verification through simulation and analysis, reflecting professional workflows commonly used in power electronics design.

Because EGR433 is typically taken near the end of the ECE curriculum, students enter the course with substantial prior exposure to analytical modeling, simulation tools, and design verification. Prior ASEE and IEEE studies have noted that senior-level design-oriented courses provide an effective setting for examining how students apply engineering judgment when interacting with advanced tools and incomplete or uncertain information [33], [34].

**2. Assignment Design and AI Integration**

AI integration in EGR433 was implemented as a one-period mini-project focused on the design of a DC-DC buck converter. Students were required to complete a traditional hand analysis to determine component values and expected operating characteristics, including duty cycle, inductor current ripple, and output voltage ripple. Students then generated an AI-assisted design using a generative AI tool and compared the two approaches.

Both manually derived and AI-assisted designs were verified using PSpice simulation, with students examining waveforms, steady-state behavior, and transient response. Students documented AI prompts and outputs and summarized results in standardized comparison tables. AI use was explicitly framed as optional and supplemental, with emphasis placed on verification and accountability for final design decisions. This structure reflects ASEE recommendations that AI use in senior-level courses be aligned with professional expectations and verification practices [35].

**3. Survey Methodology**

Pre- and post-assignment surveys were administered to assess student perceptions of AI use in a senior-level design context. Surveys used the same five-point Likert scale and constructs as other courses in this study: AI confidence, verification skill, and ethical awareness. Maintaining consistent survey constructs enabled comparison across course levels while acknowledging differences in technical complexity.

Ten students completed both the pre- and post-surveys. While the sample size was small, it reflects typical enrollment in senior-level power electronics courses and is consistent with ASEE studies conducted in advanced electives [36].

**4. Survey Results**

Table 3 summarizes the pre- and post-assignment survey results for EGR433.

**Table 3. Pre/Post Survey Results for EGR433 Power Electronics**

| Dimension | Pre Mean | Post Mean | Δ Change | Interpretation |
|---|---|---|---|---|
| AI Confidence | 3.70 | 3.88 | +0.18 | Modest increase; high baseline prior to assignment |
| Verification Skill | 4.40 | 4.25 | −0.15 | Slight recalibration reflecting increased AI skepticism |
| Ethical Awareness | 4.70 | 4.25 | −0.45 | Awareness remained high; post-survey reflects realism |

Results show a modest increase in AI confidence, consistent with students' prior familiarity with simulation and design tools. Small decreases in verification confidence and ethical awareness were observed. While these patterns may suggest a calibration effect, the small sample size (n = 10) limits strong causal interpretation. These findings should therefore be viewed as preliminary.

**5. Observations and Student Reflections**

Student reflections highlighted that AI-generated explanations often appeared confident and well-structured but occasionally relied on incorrect assumptions or oversimplified models. Several students noted that AI outputs underestimated non-ideal effects or failed to account for practical design considerations, which were revealed through simulation results. These experiences reinforced the importance of independent analysis and verification, particularly in safety- and performance-critical applications such as power electronics.

These observations align with IEEE reports indicating that AI tools can support early-stage design exploration but require careful oversight and validation in power electronics and other hardware-intensive domains [37].

Overall, the EGR433 implementation illustrates how intentional AI integration in a senior-level course can promote critical evaluation, reinforce professional verification habits, and prepare students for AI-enabled engineering workflows without compromising technical rigor.

## V. Results: Cross-Course Synthesis

This section synthesizes findings across four Electrical and Computer Engineering (ECE) courses, EGR231, EGR234, EGR333, and EGR433, spanning sophomore- to senior-level instruction. Results are drawn from a combination of pre- and post-assignment surveys (EGR231, EGR333, EGR433) and qualitative artifact analysis (EGR234). Together, these data provide complementary evidence regarding how intentional AI integration influences student confidence, verification behavior, and ethical awareness across different technical contexts and curricular stages.

### A. Trends in AI Confidence Across Course Levels

Across all courses that included survey data, students reported increased confidence in using AI tools for engineering problem-solving following structured exposure. The magnitude of this increase varied by course level and technical context. The largest increase was observed in EGR333 Electronics I, where students engaged in open-ended analog circuit design and simulation-based verification. More modest increases were observed in EGR231 Circuit Theory I and EGR433 Power Electronics, where baseline confidence was higher or where AI was introduced in a more constrained manner.

These trends suggest that AI confidence gains are influenced not only by exposure itself but also by the nature of the task. Design-oriented assignments that require iterative evaluation and adjustment appear to provide particularly strong opportunities for students to explore AI capabilities while recognizing their limitations. Similar patterns have been reported in ASEE studies examining student engagement with emerging computational tools in upper-division engineering courses [38].

### B. Verification Skill and Calibration Effects

Unlike AI confidence, changes in self-reported verification skill were mixed across courses. In EGR231, verification confidence increased slightly, reflecting reinforcement of checking and validation behaviors in a foundational analytical context. In contrast, EGR333 and EGR433 exhibited small decreases in verification confidence, despite post-survey means remaining high.

This pattern may reflect a calibration effect rather than a decline in verification ability. Exposure to AI-generated errors, oversimplified assumptions, or context-insensitive outputs may have prompted students to reassess their confidence more conservatively. However, given the variation in sample sizes across courses, particularly in upper-division offerings, these interpretations should be considered exploratory rather than confirmatory. Prior IEEE and ASEE research on human–automation interaction and educational technology adoption has similarly observed that increased awareness of tool limitations can lead to more conservative self-assessments without reducing actual competence [39], [40].

Evidence from the EGR234 qualitative case study supports this interpretation. In that course, students consistently relied on simulation waveforms and hardware behavior to validate AI-assisted designs, often identifying and correcting AI-generated errors. These behaviors indicate active verification, even in the absence of survey-based confidence measures.

### C. Ethical Awareness and Professional Responsibility

Across all surveyed courses, ethical awareness remained high both before and after AI-integrated assignments. Small decreases observed in some courses are again interpreted as calibration effects, as post-survey means remained above 4.0 on a five-point scale. Student reflections across courses emphasized increased awareness of the risks associated with unverified AI outputs and the engineer's responsibility for final decisions.

These findings align with ASEE literature suggesting that ethical awareness is most effectively reinforced when ethical considerations are embedded within technical work rather than presented as abstract principles [23]. By requiring students to document AI use, critique outputs, and verify results, the instructional approach described in this paper positioned ethical responsibility as an integral component of engineering practice.

### D. Complementarity of Quantitative and Qualitative Evidence

The combination of survey data and artifact-based analysis strengthens the overall findings of this study. Survey results capture shifts in student perceptions and self-reported confidence, while artifact analysis in EGR234 provides concrete evidence of verification behaviors and design decision-making. Together, these forms of evidence suggest that intentional AI integration can promote critical engagement rather than passive reliance.

ASEE research has emphasized the value of mixed-methods approaches in engineering education, particularly when evaluating instructional innovations across diverse course contexts [41]. The results presented here illustrate how quantitative and qualitative evidence can be combined to provide a more complete picture of student learning and behavior.

### E. Summary of Cross-Course Findings

Across four courses and multiple curricular levels, three consistent patterns emerged:

1. **AI confidence increased** following structured, assignment-based exposure.
2. **Verification behaviors appeared to be sustained across courses**, with observed calibration effects reflecting increased awareness of AI limitations.
3. **Ethical awareness remained high**, particularly when AI use was transparent and explicitly connected to professional responsibility.

These results suggest that verification-driven AI integration can be scaled across an ECE curriculum without compromising rigor, provided that assignments are carefully designed and aligned with learning objectives.

## VI. Discussion

The results of this multi-course study suggest that generative AI tools can be integrated into Electrical and Computer Engineering (ECE) coursework in ways that reinforce, rather than undermine, foundational engineering competencies. Across courses and curricular levels, structured AI exposure increased student confidence in using AI tools while sustaining strong emphasis on verification and ethical responsibility. Importantly, these outcomes were achieved without reducing analytical rigor or replacing traditional problem-solving expectations.

### A. Verification-Centered Integration as a Design Principle

A central finding across courses is the importance of verification as an explicit instructional requirement. In EGR231 and EGR333, students encountered AI-generated errors in analytical derivations or design assumptions, while in EGR234 and EGR433, limitations emerged through simulation mismatches or hardware behavior. In each context, assignments that required independent verification prompted students to identify, diagnose, and correct errors rather than accept AI outputs uncritically.

This finding aligns with ASEE and IEEE literature emphasizing that effective use of automation depends on maintaining human oversight and responsibility for outcomes [42], [43]. By positioning AI as a hypothesis generator rather than an authoritative source, the instructional framework described here supported development of engineering judgment, a core professional competency.

### B. Calibration Effects and Student Self-Assessment

The observed decreases in self-reported verification confidence and ethical awareness in some courses warrant careful interpretation. Rather than definitively indicating diminished competence, these changes may reflect calibration effects, in which increased awareness of AI limitations leads to more conservative self-assessment. However, additional data from larger cohorts and longitudinal analysis would be necessary to confirm this interpretation. As students gained experience with AI tools and encountered their limitations, they developed more realistic perceptions of their own abilities and the reliability of automated outputs.

Such calibration has been documented in prior IEEE and ASEE studies examining student interaction with advanced computational tools [41], [44]. From an educational perspective, this outcome is desirable: engineers who recognize uncertainty and limitations are better positioned to engage in critical evaluation and risk-aware decision-making.

### C. Ethical Responsibility Embedded in Technical Work

Ethical awareness remained high across all surveyed courses, particularly when AI use was transparent and explicitly linked to professional responsibility. Rather than isolating ethics as a standalone topic, embedding ethical reflection within technical assignments appeared to reinforce the notion that ethical AI use is inseparable from engineering practice.

ASEE research has consistently argued that ethics instruction is most effective when contextualized within discipline-specific tasks [23]. The findings of this study support that perspective, demonstrating that ethical considerations related to AI, such as accountability for errors and transparency of tool use, can be meaningfully addressed within core ECE coursework.

### D. Scalability Across the Curriculum

One contribution of this work is the demonstration that a common pedagogical framework for AI integration can be applied across multiple courses with different technical content and instructional goals. While specific assignments varied, the shared emphasis on verification, documentation, and reflection enabled consistent messaging regarding responsible AI use.

This scalability is particularly important for ECE programs seeking to respond to AI-related challenges without overhauling curricula. Prior ASEE studies on curricular innovation suggest that incremental, coherent changes are more sustainable and effective than isolated interventions [8]. The approach described here provides a practical model for program-level AI integration.

### E. Limitations

Several limitations should be acknowledged. First, survey data relied on self-reported measures, which may not fully capture actual skill development. Second, sample sizes varied across courses, particularly in upper-division offerings with smaller enrollments. Third, implementations were conducted within a single institution, which may limit generalizability.

Despite these limitations, the use of mixed methods, combining survey data with artifact-based analysis, strengthens the validity of the findings. ASEE literature supports such approaches when evaluating instructional innovations in authentic classroom settings [45].

Because survey sample sizes were modest and response rates varied between pre- and post-measures, statistical significance testing was not emphasized, and findings should be interpreted as indicative trends rather than definitive outcomes.

### F. Implications for ECE Educators

For ECE educators, these findings suggest that the central question is not whether AI tools should be acknowledged, but how they can be incorporated responsibly. Requiring verification, promoting transparency, and embedding ethical reflection within technical work can help ensure that AI enhances learning while preserving rigor and professional standards.

## VII. Conclusion

This paper presented a multi-course, evidence-based examination of structured generative AI integration within an ECE curriculum. Across four courses spanning sophomore- to senior-level instruction, AI tools were incorporated into existing assignments using a common pedagogical framework that emphasized verification, engineering judgment, transparency, and ethical responsibility. Rather than treating AI as a replacement for traditional problem-solving, the approach positioned AI as a supplemental resource whose outputs must be critically evaluated.

Results from pre- and post-assignment surveys in three courses, complemented by qualitative artifact analysis in a digital logic laboratory, indicate that structured exposure to AI tools can increase student confidence while sustaining strong verification habits and ethical awareness. Observed shifts consistent with calibration effects suggest that students developed more realistic perceptions of AI capabilities and limitations, an outcome consistent with professional engineering practice.

A key contribution of this work is the demonstration that a verification-driven approach to AI integration can be scaled across diverse technical contexts without compromising rigor. By embedding AI use within core coursework and aligning assignments with established learning objectives, educators can prepare students for AI-enabled professional environments while reinforcing foundational engineering competencies.

As generative AI tools continue to evolve, engineering education must adapt in ways that are both responsible and pedagogically sound. The findings presented here suggest that intentional, structured integration grounded in verification and ethical accountability, offers a practical path forward for ECE programs seeking to balance innovation with professional standards.

Future work will examine longitudinal outcomes and larger cohorts to determine whether observed calibration patterns persist as students gain extended experience with AI tools.

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