WIP: Evaluating a Course-Specific AI Assistant to Support Learning in an Electromagnetics Course

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Prof. Chen teaches a wide range of undergraduate and graduate courses across the electrical engineering curriculum, including engineering electromagnetics, probability, electronic circuits, microwave engineering, and analog signal processing. He is a dedicated and effective educator who has been recognized multiple times on the University of Illinois's List of Teachers Ranked as Excellent by Their Students. Prof. Chen

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WIP: Comparing Course-Specific and General-Purpose AI Integration in Undergraduate ECE Education

1. Introduction

In recent years, generative artificial intelligence (AI) tools have rapidly become widespread in undergraduate engineering education. An increasing number of students are using tools such as ChatGPT, Copilot, and Gemini etc. during their studies to obtain explanations, derive problem-solving steps, or understand unfamiliar concepts. In Electrical and Computer Engineering (ECE) courses, students need to master both mathematical derivations and conceptual understanding at the physical or system level. The widespread use of AI tools in this learning environment presents new possibilities but also introduces new challenges. AI may improve learning efficiency and engagement; however, if students use AI carelessly, its incorrect explanations, fabricated reasoning, and potential weakening of conceptual understanding could negatively impact learning outcomes.

Therefore, an increasing number of engineering educators are exploring how to incorporate AI tools into curriculum design to facilitate learning, rather than replace it. However, current discussions about the application of AI in education often focus on what AI tools can do, with less attention paid to how instructors can guide students in using AI. In fact, the same AI tool, under different instructional guidance, can lead to substantially different learning behaviors. For example, AI can be viewed as a general problem-solving tool, a concept explainer, or a learning assistant closely integrated with course content. These different perspectives can influence students' trust in AI, their verification behaviors, and their learning approaches.

This paper is a work-in-progress (WIP) study. We aim to investigate how different approaches to AI instruction influence undergraduate ECE students' use of AI, their trust in it, their verification behaviors, and their perceptions of its learning value. This research was conducted in two undergraduate ECE courses. In the 300-level required course, ECE 329, AI was designed and presented as a course-specific learning assistant, which was trained using course materials and closely integrated with the course content. In another 200-level core course, ECE 210, AI was presented as a general problem-solving tool, with a focus on solution verification, tool comparison, and learning reflection.

This paper does not aim to evaluate the performance or merits of any specific AI tool. Instead, this study focuses on how students interact with AI tools in different instructional contexts. By using the same survey questionnaire and reflection questions in two courses, this paper attempts to provide preliminary insights into how instructional design choices influence students' AI usage behavior. The results of this study will provide guidance for the design of future AI integration into ECE curricula and lay the foundation for developing more pedagogically valuable and responsible guidelines for AI use.

2. Background and Related Work

In recent years, the field of engineering education has begun to study the impact of generative AI on student learning. Several studies [1, 2] indicate that engineering students are using AI tools to understand concepts or solve problems. Existing literature [3] generally suggests that AI tools can help students by quickly providing explanations for complex or unfamiliar content. However, AI-generated responses may contain errors, incomplete reasoning, or even fabricated information.

Furthermore, some studies [3, 4] indicate that overreliance on AI may decrease students' engagement and pose a risk to academic integrity.

These problems are particularly noticeable in Electrical and Computer Engineering (ECE) education. ECE courses not only involve many abstract concepts and mathematical derivations but also require students to connect mathematical concepts with their physical meaning. In this way, if students use AI tools without critical thinking, AI may hide misunderstandings rather than support learning. As a result, guiding students to use AI appropriately in ECE courses becomes an important pedagogical challenge.

Existing research has focused on students’ attitudes towards AI and trust in AI tools. For example, one study [5] investigated first-year engineering students’ attitudes towards ChatGPT and found that students had positive views of AI generally. However, the study also revealed that students were overconfident in the accuracy of AI outputs. In addition, the students had different understandings of the ethical boundaries of how to use AI tools. Similarly, another study [6] used questionnaires to assess engineering students’ perceptions of AI tools’ role in learning. The results showed that students generally agreed that AI tools could improve learning efficiency and provide explanations. These studies mainly focus on students’ perspectives rather than discussing how pedagogical design affects students’ use of AI tools.

Other studies have explored how to practically embed AI tools into courses. One study [7] developed course-specific chatbots to support students in finding course-related information, like homework or exam schedules, and learning resources. This work showed that course-specific AI tools may improve students’ access to course resources and reduce repetitive tasks from instructors or teaching assistants (TAs). However, this work has limited examination on how students could critically use AI output and how instructional guidance may impact the learning experience.

Other research has guided students to use AI tools through structured assignments. For example, one study [8] used AI extra credit assignments in an engineering economics course. Students were asked to compare their manual solutions with AI-generated output and identify their differences. These studies show that combining AI usage with verification and reflection can play a positive role in learning [9]. However, these studies typically focused on a single course rather than comparing different AI integration strategies in teaching effectiveness. Similar work of verification-based approaches without AI, like allowing students to re-submit assignments after correcting errors, have also been shown to support learning and understanding [10].

Despite the increasing number of studies on AI usage in engineering education, there is a lack of research directly comparing the effects of course-specific AI tools and generic AI tools in ECE courses. This paper aims to provide a preliminary investigation of how two AI integration strategies affect students’ engagement and verification behaviors.

3. Course Contexts and Instructional Design

This study was conducted in two undergraduate ECE courses at the University of Illinois Urbana-Champaign. Both courses included optional extra-credit AI assignments and used similar reflective surveys to collect student feedback. However, the AI assignments were implemented differently between the two courses. This section will describe the different approaches used in each course and explain the pedagogical design considerations behind each strategy.

3.1 ECE 329 course: Course-Specific AI Integration

The ECE 329 course is a technical elective upper-level undergraduate course covering electromagnetic fields and Maxwell's Equations, electromagnetic wave propagation, transmission lines, etc. Students often face various difficulties when studying this course, including but not limited to the abstract nature of the course content, demanding mathematical derivations, and the challenge of connecting math formulas with their physical meanings. To support student learning, this course has introduced a course-specific AI assistant closely integrated with the course content.

The course-specific AI assistant was trained with course materials, including syllabus, lecture slides, homework sets, and lecture recordings. The integration of the course-specific AI assistant offers several key benefits for students. Firstly, students can receive immediate feedback on general questions related to the syllabus and lecture content, whereas they used to ask questions in a class forum, and it may take hours to get an answer. Secondly, because the AI assistant is trained with all the course materials, it can direct students to the specific location of a topic within the lecture notes, as well as provide the corresponding timestamps in recorded lectures. Thirdly, the AI assistant will not use general information outside of the course material from the web, and therefore, there is less chance of generating incorrect answers. Lastly, instructors have control over the level of detail provided in homework problems. While the tool can generate step-by-step solutions like other generative AI tools, instructors have configured it to offer general guidance instead of revealing detailed answers [11]. This approach helps students engage with the material more deeply and prevents them from copying and pasting answers when completing homework assignments.

The course-specific AI tool was introduced at the start of the semester. At the end of the semester, we designed an optional extra-credit assignment. Students were encouraged to use both the course-specific AI tool and general AI tools to solve the same problems and then compare them. A survey was designed to consider the AI tools' accuracy, clarity, usefulness, and students' trust of the AI's answers. We also encouraged students to focus on how the course-specific AI tool's functional limitations impacted their learning experience. In the ECE 329 course, the course-specific AI tool was positioned as a learning aid, aiming to help students understand concepts and encourage engagement with the course material.

3.2 ECE 210 course: Public AI Tools

The ECE 210 course is a core undergraduate course that focuses on topics such as analog system analysis, Fourier series, Fourier transform, convolution, frequency response. Compared to the ECE 329 course, this course has a stronger emphasis on procedural problem-solving and analytical methods. Based on these course characteristics, the AI tool was not designed as a course-specific tool in this course, but rather as a general problem-solving resource.

At the end of the semester, we asked students to complete an optional extra-credit assignment that required them to use publicly available AI tools (such as ChatGPT, Copilot, Gemini). Students were asked to have the AI tools answer a few signal processing problems and then evaluate the generated solutions. The assignment explicitly required students to verify the correctness of the solutions, compare the answers from different tools, and identify any errors or ambiguities.

Unlike the assignment in the ECE 329 course, the ECE 210 course assignment did not require students to use AI for syllabus lookup or course content navigation. Instead, the assignment emphasized that students should verify the accuracy of AI-generated solutions and identify any mistakes or ambiguous explanations. Students were then asked to reflect on how using AI affected their comprehension, confidence, and approach to problem-solving. In this course, AI was treated as an external tool, and its educational value depended on whether students could evaluate its output carefully and use it responsibly.

4. Research Questions and Study Design

This study aims to explore how different approaches to integrating AI into teaching affect undergraduate ECE students' use of AI tools and their learning experiences. The study focused on instructional design, not on the performance of specific AI tools. The research questions (RQ) are:

RQ1: Are there any differences in how students use course-specific AI and a publicly available AI tool?

RQ2: How do different AI instruction approaches affect students' trust in AI outputs and their verification behaviors?

RQ3: How do students perceive AI's support for learning and problem-solving under different AI integration strategies?

The research data were collected through anonymous questionnaires at the end of the semester. Similar questionnaires and reflection questions were used for both courses to allow for comparative analysis across different teaching contexts. The questionnaire included questions about the frequency of AI use, level of trust in AI, verification behaviors, and learning perceptions, as well as included open-ended questions to collect students' reflective feedback.

5. Survey Data Analysis and Results

The data for this study were collected from an optional extra-credit activity in two undergraduate ECE courses. ECE 210 had a total enrollment of 364 students in the Fall 2025 semester, with 316 students consenting to the use of the questionnaire, resulting in a participation rate of approximately 86.8%. ECE 329 had a total enrollment of 202 students, of whom 177 completed the questionnaire, with a participation rate of approximately 87.6%.

After the bonus points were recorded, all data used for research and analysis were de-identified. All subsequent statistical analyses were based on anonymous data.

5.1 RQ1: AI Usage Frequency and Course Differences

Research Question 1 explores the differences in students' use of course-specific AI and generative AI tools in their overall learning context and in these specific courses. To answer this question, this study used two questions, Q6 and Q7, to measure students' "AI usage frequency in overall learning scenarios" and "AI usage frequency in this course," respectively. Figure 1 shows students' responses on AI tool use frequency in their daily activities, including the number of counts in each category and the percentage. This showed that most students frequently used generative AI tools in their daily studies.

Regarding "overall frequency of use" (Q6), only about 7.5% of students reported never using AI tools, about 21.7% used them about once a week, about 36.2% used them several times a week, and about 10.7% used them daily. Overall, more than two-thirds of students used AI at least "once a week."

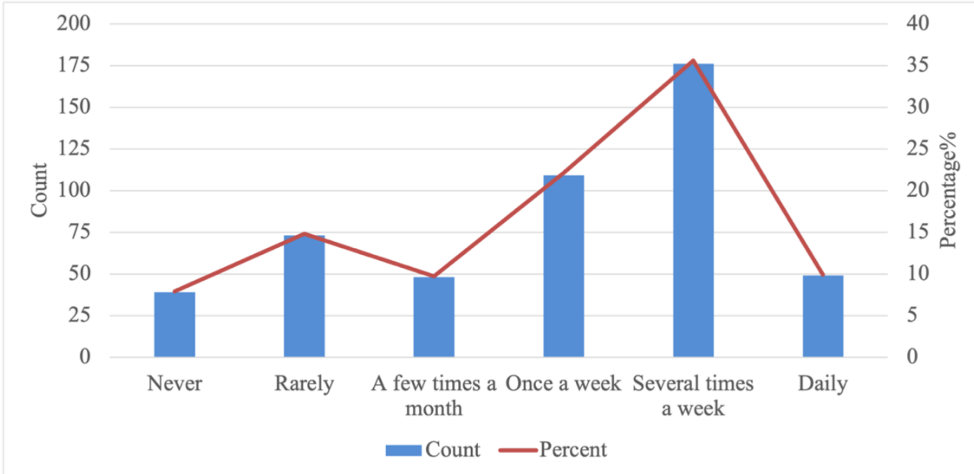

Figure 1. Frequency with which students used AI tools in their daily activities.

The next question examined students' AI usage frequency in the course (Q7). As shown in Figure 2, usage was concentrated in the higher-frequency range. Only about 2% of students never used AI in this course, about 34.8% used it "several times a week," and about 37.7% used it daily. This indicated that once AI is explicitly incorporated into course activities, students' actual frequency of use in that course increases significantly.

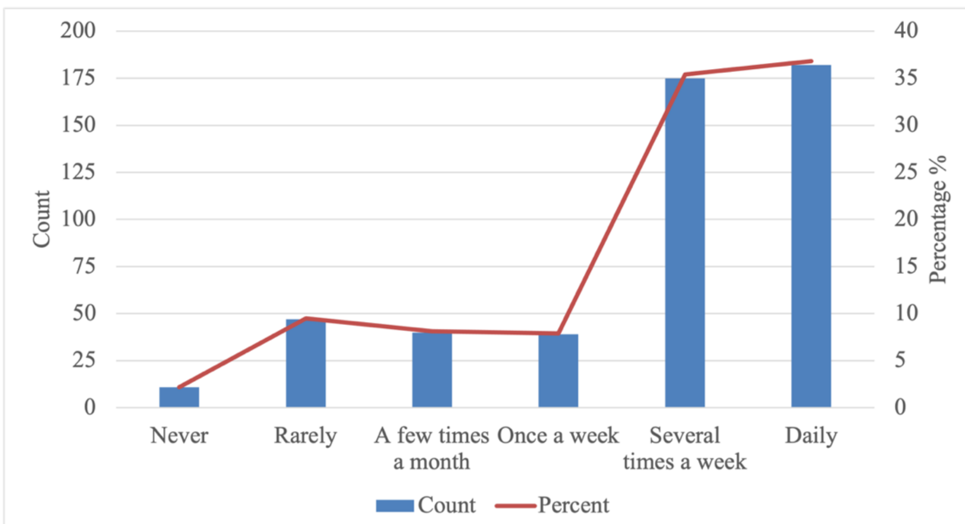

Figure 2. Students' responses on the frequency with which they used AI tools in the courses.

Subsequently, a contingency table and chi-square test were used to compare the frequency distributions of AI usage in the two courses. The comparison results between the two courses indicate a statistically significant difference in the overall frequency distribution of AI tool usage, but the difference is not significant in terms of "frequency of use in this course".

For Q6, the chi-squared test of the contingency table for course and overall usage frequency yielded $\chi^2(5) \approx 14.01$, $p = 0.016$. Students in ECE 329 had a slightly higher proportion of "several times a week" usage, while students in ECE 210 had slightly higher proportions of "never used" and “rarely used”. This suggests that higher-level students were relatively more accustomed to using AI tools before participating in this study.

For Q7, the chi-square test examining the relationship between the course and the “frequency of use in this course” yielded $\chi^2(5) \approx 4.87$, $p = 0.43$, indicating no significant difference. Approximately 70% of students in both courses reported using AI “several times a week” or “almost daily” in this course, showing a very similar distribution.

Overall, the results of RQ1 provide two findings. First, most students in the sample were already frequent users of generative AI, with high usage rates in both general learning and specific courses. Second, although senior students used AI more frequently overall before entering the courses, under the AI activities designed in this study, the actual usage frequency in both courses tended to be similar. This provides a comparable basis for subsequent comparisons of AI experiences under two different teaching approaches (RQ2 and RQ3).

5.2 RQ2: Students’ Trust and Verification Awareness Regarding AI

RQ2 focuses on the following questions: What are students’ attitudes toward trusting AI tools and the importance of verifying AI outputs in their courses? Do the different teaching approaches of various courses influence these attitudes?

Table 1 summarizes the descriptive statistics for all multiple-choice items related to students’ perceptions of AI tools. All items were measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Overall, the average scores for all questions were above the midpoint of the scale (3), indicating that students generally held positive attitudes towards the role of AI tools in learning. Questions related to “learning support” and “ease of use” received particularly high scores. For example, the average score for “AI helps in understanding course concepts” (Q10) was approximately 4.03, and the average score for “AI tools are generally easy to use” (Q8) was approximately 3.98. These results suggest that most students recognize the value of AI in helping them understand course content.

Table 1. Descriptive statistics for AI-related survey items (Q8 – Q19).

No.	Item	Mean	Standard Deviation (SD)
Q8	AI tools were generally easy to use	3.98	0.967
Q9	AI tools provided accurate information about course content.	3.61	0.925
Q10	AI tool clarified course concepts	4.04	0.972
Q11	I think AI is generally accurate in solving course problems	3.29	1.048
Q12	Rephrasing prompt improved output	3.52	0.967
Q13	Comparing AI tools helped me see AI limitations	3.62	0.981
Q14	I trust AI tool outputs	3.36	1.112
Q15	AI tools made me clearer about topics	3.36	1.033
Q16	I’m likely to use AI tools in other future courses	3.28	1.014
Q17	I am satisfied with AI tools	3.73	0.938
Q18	I think verifying AI output is important	4.56	0.79
Q19	Using AI may raise concerns about academic integrity and responsible use	4.26	0.969

Meanwhile, students did not express complete trust in AI tools. Questions related to accuracy and limitations showed a more neutral attitude. For example, the average score for "I think AI is generally accurate in solving course problems" (Q11) was approximately 3.29, slightly above the midpoint.

Furthermore, questions related to potential risks received higher scores. The average score for "I realize the need to verify AI's answers using course materials or my own knowledge" (Q18) was 4.56, and the average score for "Using AI may raise concerns about academic integrity and responsible use" (Q19) was 4.26. This indicates that while students generally use and appreciate AI tools, they are also clearly aware of the importance of verification and responsible use.

To compare whether there were differences in student attitudes across different instruction methods, we further compared selected individual questions between the two courses. Table 2 compares selected AI-related survey items between the two courses. For each item, mean scores and standard deviations are reported, along with results from independent-samples *t*-tests. The results indicate that for questions related to trust, such as Q11 (accuracy of AI) and Q14 (trust in AI to help understand concepts), the mean differences between ECE 210 and ECE 329 were not significant, and the corresponding effect sizes were small. However, for questions related to verification awareness of the importance of verifying AI-generated output (Q18), the difference was statistically significant ($p = 0.026$). ECE 210 students rated Q18 higher than ECE 329 students. This may be because ECE 210 students were using a generic AI tool while ECE 329 students were using a course-specific AI tool.

Table 2. Comparison of selected AI-related survey items between courses for RQ2 (*$p < 0.05$).

	ECE 210 (N=316)		ECE 329 (N=177)		
Item	**Mean**	**SD**	**Mean**	**SD**	**p-value**
Q11	3.28	1.09	3.33	0.96	0.594
Q14	3.29	1.14	3.47	1.04	0.086
Q18	4.62	0.75	4.45	0.85	0.026*

5.3 RQ3: The Relationship Between Perceived Learning Value, Satisfaction, and AI Usage Behavior

RQ3 explores the following questions: How do students perceive the learning value of AI, their overall satisfaction with it, and their intention to use it in the future? How do these results relate to students' trust attitudes, verification awareness, and frequency of AI use?

As shown in Table 3, mean scores and standard deviations for selected AI-related survey items were compared between the two courses using independent-samples t-tests. Overall, the two courses exhibited a high degree of consistency across most survey questions. For the three items: "Does AI help in understanding course concepts?" (Q10), "Would you be willing to use AI in other courses in the future?" (Q16), and "Overall satisfaction" (Q17), the average scores for ECE 210 and ECE 329 did not differ significantly. This suggests that the different pedagogical approaches to AI in the two courses did not significantly alter students' evaluation of the value of AI in learning and their overall experience.

Table 3. Comparison of selected AI-related survey items between courses for RQ3 (*$p < 0.05$).

	ECE 210 (N=316)		ECE 329 (N=177)		
Item	**Mean**	**SD**	**Mean**	**SD**	**p-value**
Q10	4.02	1.02	4.06	0.88	0.662
Q16	3.22	1.05	3.36	0.94	0.151
Q17	3.72	0.96	3.75	0.91	0.729
Q19	4.34	0.93	4.12	1.03	0.020*

The question "AI may raise concerns regarding academic integrity and responsible use" (Q19) approached statistical significance ($p < 0.05$). ECE 210 students scored slightly higher on both items than ECE 329 students. These results indicate that students in both courses generally had a basic understanding of the potential impacts of using AI. Students in ECE 210, which emphasized the use and verification processes of generative AI tools, showed slightly higher levels of concern regarding future usage and academic integrity.

In terms of correlation analysis, the results in Table 4 showed a clear and consistent pattern. First, there was a moderate positive correlation between the frequency of students' use of AI in the course (Q7) and several learning outcome variables. For example, Q7 showed significant positive correlations with Q10 (learning assistance), Q16 (willingness to use in the future), and Q17 (overall satisfaction), indicating that students who used AI more frequently in this course tended to appreciate its learning value more and were more satisfied with the overall experience.

Table 4. Spearman correlations between AI usage frequency vs. trust/verification attitudes and learning-related outcomes.

Variable 1	Variable 2	Spearman r	p-value
Q7	Q10	0.467	< 0.001
Q7	Q16	0.332	< 0.001
Q7	Q17	0.430	< 0.001
Q7	Q19	-0.097	0.031
Q11	Q10	0.335	< 0.001
Q14	Q10	0.469	< 0.001
Q18	Q17	0.214	< 0.001
Q18	Q19	0.457	< 0.001

Items related to attitudes also showed similar trends. Students' trust in the accuracy and reliability of AI (Q11 and Q14) showed a moderate positive correlation with perceived learning assistance and satisfaction. Meanwhile, questions related to verification awareness (Q18) were not only positively correlated with learning assistance and satisfaction but also positively correlated with concerns about academic integrity (Q19). This suggests that students who emphasize verifying AI output both benefit from AI in their learning and are more aware of its potential risks.

6. Discussion

This study focused on two AI integration methodologies in two ECE courses. We explored the relationships between students' AI usage frequency, satisfaction, motivation, verification attitudes, and learning experience regarding AI tools.

6.1 AI Use Frequency and Students' Learning Experience

Based on students' feedback, AI use frequency and students' attitudes towards AI tools were positively correlated. Students who used AI more frequently tended to be more positive, in terms of whether AI helped them understand course content, as well as overall satisfaction and future willingness to use AI. This suggests that students are more likely to use AI tools as a learning resource when they engage with them more regularly.

6.2 Similarities and Differences in Student Attitudes Under Different Teaching Frameworks

Students showed similar trends in their evaluations across most survey questions. The mean values of the two groups of students (ECE 210 with course-specific AI tools and ECE 329 with generic AI tools) did not show significant differences. This result suggests that different AI integration strategies in teaching did not significantly affect students' overall judgment of the usefulness of AI integration techniques.

6.3 Verifying the Relationship Between Trust and Academic Integrity

This study identified some trends related to verification awareness and academic integrity concerns. The findings showed a moderate positive correlation between students' recognition of the importance of validating AI output and their concern about academic integrity. This implies that instructional frameworks focusing on verification and critical evaluation may help students develop a clearer understanding of the potential risks of AI use.

6.4 Educational Implications

In general, the results suggest that different AI integration strategies were associated with largely similar student perceptions of learning experience. Their educational value may largely depend on how students are guided during teaching. It may be more effective to instruct students to utilize AI as a learning tool that requires verification, rather than as an "answer generator" that replaces the learning process [6]. This helps improve students' critical thinking and sense of responsibility.

For engineering educators, this means that when introducing AI into the course, they should focus on helping students develop reasonable expectations. It is more necessary to carefully plan course assignments, reflective questions, and usage guidelines than to consider whether or not to allow or prohibit the use of AI.

6.5 Limitations and Future Work

This research has several limitations. First, the study relies on student self-reported data and does not directly measure learning outcomes or long-term behavioral changes. Additionally, this study primarily focuses on student attitudes and perceptions within one course. Differences among student groups were not considered.

Future work will further expand and incorporate qualitative data (such as interviews or open-ended reflections) to explore in greater depth students' actual learning behaviors and decision-making processes. The research team also plans to expand this work into more courses and evaluate the long-term impact of AI integration in engineering education.

7. Conclusion

This paper explores the relationship between students' usage and learning experience regarding AI in two ECE undergraduate courses. This study provides preliminary results for understanding how AI tools can be integrated into engineering education.

The research findings indicate that more frequent use of AI tools in the courses is associated with more positive evaluations of usefulness, higher satisfaction, and greater willingness to use AI in the future. However, students who experienced different AI integration strategies in the two courses showed high consistency in their feedback. This suggests that variations in the AI instruction did not significantly affect students' overall perceptions of AI tools. Also, the findings suggest that instructional designs emphasizing critical verification and responsible use may help students develop a clearer understanding of academic integrity issues related to AI use.

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