Student Attitudes and Perceptions of AI and AI-Generated Practice in the Classroom

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Abstract

Despite the prevalence of AI tools, research is still emerging on how students perceive them and use them in their studies. Faculty teaching three courses at Iowa State University used AI-generated practice alongside the etextbook as a low-stakes homework assignment. While prior research on this practice has found it effective for learning, it was important to better understand how students perceive and use AI generally, in addition to this specific tool. In this investigation, 234 students across three courses responded to end-of-semester survey to capture their course perceptions, general comfort and trust levels with AI, frequency of use, types of use, and perceptions of the AI-generated questions more specifically. Survey findings suggest that student usage and attitudes toward AI remains varied. While a small portion of learners appear comfortable integrating AI tools into their studies, many remain infrequent users of such technology, with the most frequent use for AI being spelling and grammar support. It is key for those in higher education and educational technology alike to keep in mind that the ease of access and pervasiveness of AI tools does not equate to ubiquitous student use, mastery, or sophisticated learning strategies. In light of these survey findings, the need for effective AI tools for classroom implementation as well as general AI literacy strategies for teaching and learning are discussed.

Keywords: formative practice, artificial intelligence, automatic question generation, student perception

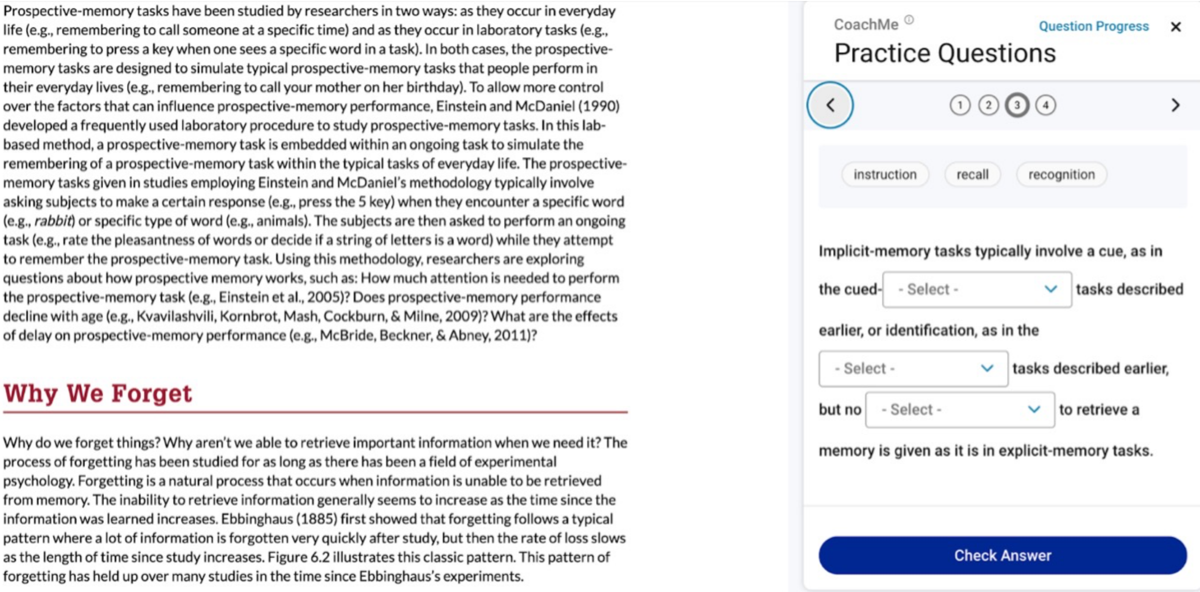
Introduction

A substantial body of prior research has demonstrated that formative practice improves learning outcomes across disciplines, with particularly strong benefits for students who are struggling (Black & Wiliam, 2010). As it functions as no- or low-stakes practice testing, formative practice is one of the most effective and well-supported study strategies (Dunlosky et al., 2013). Formative practice is defined here as questions that support students in monitoring their comprehension and learning. These questions are generally ungraded or low stakes, provide immediate feedback, and allow students to attempt them repeatedly without penalty.

The connection between formative practice and learning is further clarified through research on the doer effect conducted by Carnegie Mellon University's Open Learning Initiative (OLI). Advances in digital learning environments have enabled the collection of large-scale, fine-grained learning data (Goldstein & Katz, 2005), allowing longstanding educational questions to be revisited using new analytical approaches (Fischer et al., 2020). In these environments, every learner interaction is captured as clickstream data, making it possible to disentangle the effects of reading and doing. Using OLI courseware data that included reading, doing, and video watching behaviors, Koedinger et al. (2015, 2016) found that engaging in practice was approximately six times more effective for learning than reading alone. Subsequent analyses established that this doer effect reflects a causal relationship between doing and learning (Koedinger et al., 2016; Koedinger et al., 2018). Follow-up replication studies reproduced both the correlational and causal findings, supporting the robustness and generalizability of this effect across contexts (Van Campenhout et al., 2021a; Van Campenhout et al., 2022; Van Campenhout et al., 2023b).

In recent years, automatic question generation (AQG) systems have emerged that employ diverse techniques and serve a wide range of instructional goals (Kurdi et al., 2020). However, much of the existing research on automatically generated (AG) questions has not incorporated student interaction data, and Kurdi et al.'s systematic review found no established gold standard for evaluating question quality or performance (2020). To extend the benefits of the doer effect to a broader population of learners, an artificial intelligence–based AQG system was developed to generate formative practice directly from textbook content. The AG questions referred to in this work have been empirically validated using student data collected in authentic learning settings, contributing to the development of performance benchmarks for AG formative practice. Prior large-scale studies have compared AG questions with human-authored items on measures including engagement, difficulty, persistence (Van Campenhout et al., 2023a), and discrimination (Johnson et al., 2022); established stable performance benchmarks using over 24 million student–question interactions (Van Campenhout et al., 2021b; Van Campenhout et al., 2025a); analyzed student interaction behaviors (Van Campenhout et al., 2023c) and the effectiveness of AG feedback (Van Campenhout et al., 2024b); and examined classroom implementations of these questions (Van Campenhout et al., 2024a). Most significantly, research on these AG questions were able to replicate the doer effect research, proving for the first time that AI-generated questions could similarly generate the doer effect for students (Van Campenhout et al., 2025c).

Figure 1
An Example of a Formative Practice Question in a Textbook


Prospective-memory tasks have been studied by researchers in two ways: as they occur in everyday life (e.g., remembering to call someone at a specific time) and as they occur in laboratory tasks (e.g., remembering to press a key when one sees a specific word in a task). In both cases, the prospective-memory tasks are designed to simulate typical prospective-memory tasks that people perform in their everyday lives (e.g., remembering to call your mother on her birthday). To allow more control over the factors that can influence prospective-memory performance, Einstein and McDaniel (1990) developed a frequently used laboratory procedure to study prospective-memory tasks. In this lab-based method, a prospective-memory task is embedded within an ongoing task to simulate the remembering of a prospective-memory task within the typical tasks of everyday life. The prospective-memory tasks given in studies employing Einstein and McDaniel's methodology typically involve asking subjects to make a certain response (e.g., press the 5 key) when they encounter a specific word (e.g., *rabbit*) or specific type of word (e.g., animals). The subjects are then asked to perform an ongoing task (e.g., rate the pleasantness of words or decide if a string of letters is a word) while they attempt to remember the prospective-memory task. Using this methodology, researchers are exploring questions about how prospective memory works, such as: How much attention is needed to perform the prospective-memory task (e.g., Einstein et al., 2005)? Does prospective-memory performance decline with age (e.g., Kvavilashvili, Kornbrot, Mash, Cockburn, & Milne, 2009)? What are the effects of delay on prospective-memory performance (e.g., McBride, Beckner, & Abney, 2011)?

Why We Forget

Why do we forget things? Why aren't we able to retrieve important information when we need it? The process of forgetting has been studied for as long as there has been a field of experimental psychology. Forgetting is a natural process that occurs when information is unable to be retrieved from memory. The inability to retrieve information generally seems to increase as the time since the information was learned increases. Ebbinghaus (1885) first showed that forgetting follows a typical pattern where a lot of information is forgotten very quickly after study, but then the rate of loss slows as the length of time since study increases. Figure 6.2 illustrates this classic pattern. This pattern of forgetting has held up over many studies in the time since Ebbinghaus's experiments.

However, student perceptions and attitudes can influence the success of these questions through engagement. One study on formative practice found students can undervalue practice as a learning tool (Carvalho et al., 2017). The addition of AI learning tools only adds layers of complication surrounding perception and use. Despite its prevalence, Kelly et al. (2023) point out that research specifically examining student perceptions of AI in learning contexts is still emerging. Some studies surveying students' perceptions of AI discovered relatively low usage and experience with the technology, lack of understanding of the tools' strengths and weaknesses, and low confidence in their application for learning (Chan & Hu, 2023; Smolansky et al., 2023). Another study of higher education students from the same time period found 70% of students and faculty used generative AI tools less than once a week (Kim et al., 2025). Qualitative research using student focus groups found that students perceived the most beneficial aspects of AI to include academic support and increased efficiency, however, major concerns and anxieties remained surrounding academic integrity, inequity, decreased ability to learn and be creative, and unclear university policies (Tierney et al., 2025). Not only is it important to learn how students view formative practice in general, the cultural focus on AI also makes it necessary to gain a sense of how students view AI-generated questions. While the development work to create effective learning tools is significant and the validation of the tool using data is critical for early interpretation of its success, student perception is equally important to understand and address.

In this paper, student perceptions of AI-generated formative practice were gathered from three courses at a major higher education institution in the fall of 2024. While the faculty had two years of experience teaching with these AI questions as part of their courses, the broader explosion of generative AI raised new questions on what students were thinking and doing. This motivated researchers to ask the following questions:

1. How do students perceive AI generally?
2. How do students use AI in their studies?
3. How do students perceive formative practice once they know it was AI?

Methods

Faculty had previously taught several semesters using the AI generated practice, establishing successful implementation practices (Van Campenhout et al., 2024a). Faculty assigned textbook chapters and the corresponding practice questions on a weekly basis, with a small percent of students' grade determined by completing a minimum of 80% of the practice. Note that this score is completion—not accuracy—based to maintain the nature of low-stakes formative practice.

At the end of the semester, faculty provided students with a link to a survey aimed at gathering feedback and descriptive information on student perceptions of the questions. To encourage honesty, the survey was completely anonymous. Because the survey sought informal feedback rather than measuring a specific psychological construct, no formal psychometric validation was undertaken. This approach is consistent with prior end-of-semester feedback practices, which aim to gauge overall impressions rather than provide a high-stakes assessment.

Results and Discussion

The survey participation rates were 27% (13 of 47 students) for CJ, 76% (157 of 205 students) for COM, and 100% (64 of 64 students) for FAM. The initial portion of the anonymous survey was to gather preliminary information from students to provide context for their later responses. This included asking about their perceived difficulty of the course, expected grade, and digital versus print book preferences. This is useful context setting to better understand how students feel about their course and materials. For example, there is typically a small portion of students who strongly prefer print to digital books, and this same portion of students typically report less favorable attitudes toward the practice questions (Van Campenhout et al., 2025b). This was the case for these courses, where 15.4%, 2.9%, and 1.4% of students preferred digital much less than print, contrary to the majority of their peers. Tables 1 and 2 show results related to students' general perception of all CoachMe questions as formative practice. When asked if they thought that generally doing practice while reading is helpful for learning, the majority of students said yes, with a smaller group unsure, and a few students saying no. Note that the 15.4% who said no for CJ was the same portion who disliked digital books compared to print. Students were then asked if they found the CoachMe practice questions helpful for learning. This is an important distinction from a general attitude toward the learning method, as students could find a method beneficial but not necessarily this specific application. Table 2 shows the majority of students found it very or moderately helpful, with again, only a small portion finding them not helpful. These results are consistent with those from previous semesters of these same courses (Van Campenhout et al., 2025b).

Table 1
Student Perceptions of Practice Questions as a Learning Tool

In general, do you think doing practice questions while reading is helpful for learning?	Yes	Maybe	No
CJ	61.5	23.1	15.4
FAM	79.4	16.2	4.4
COM	73.2	22.9	3.9

Table 2
Helpfulness Ratings of Practice Questions for Studying and Assignments

How helpful did you find the practice questions for studying and preparing for assignments?	Very Helpful	Moderately Helpful	Somewhat Helpful	Not at all Helpful
CJ	38.5	30.8	30.8	
FAM	36.8	45.6	13.2	4.4
COM	34.0	37.8	23.7	4.5

Students were also asked about their comfort level with AI and how they utilize AI in their life. Table 3 shows students' comfort/trust level for each of the three courses. The results show a roughly normal distribution with few students selecting not at all or extremely comfortable, and the majority of students in the course selecting the mid comfort level. Table 4 shows the responses for how often students use generative AI tools. Similarly, few students selected often or never, and most selected sometimes or seldom.

Table 3
Student Comfort and Trust Levels With AI

How would you rate your comfort/trust level with AI?	1 Not at all comfortable	2	3	4	5 Extremely Comfortable
CJ	7.7	7.7	69.2	7.7	7.7
FAM	-	26.5	41.2	27.9	4.4
COM	5.1	10.9	37.8	32.1	14.1

Table 4
Frequency of Generative AI Usage by Students

How often do you use generative AI tools (such as ChatGPT)?	Often	Sometimes	Seldom	Never
CJ	-	23.1	61.5	15.4
FAM	7.4	36.8	35.3	20.6
COM	11.5	50.3	28.0	10.2

Students were also given an open-ended question where they were asked to describe how they used generative AI, with a reminder that their responses were anonymous. Besides some students noting they do not use generative AI at all, the most common use students cited was for help with grammar, spelling, and formatting for their writing. Several students stated that they use it to get new ideas and brainstorm for assignments. A few students cited more sophisticated learning uses such as generating practice questions or getting new explanations for concepts they didn't understand.

Students were then informed that the practice questions were generated using AI and asked if they knew that prior to using them. Despite faculty's knowledge and a note accompanying question feedback that was generated with AI, nearly all students did not realize they were AI-generated (100%, 91.2%, and 82.5% for each course respectively). Students were then asked if knowing they were AI-generated changed their perception of the questions. The results in Table 5 show the majority of students felt they were just as useful as before (69.2%, 73.5%, and 71.3% of students in each course respectively). A small portion of students felt they were more beneficial after learning they were AI-generated, while a larger portion of students felt they were less beneficial. This information adds a layer of complexity to student perception of AI when considered with to their initial thoughts on the questions.

Table 5
Effect of AI Origin on Perceived Usefulness of Practice Questions

Does knowing they were created using AI (rather than by professors, for example) make you feel differently about their usefulness?	I feel the same way	I feel they are more beneficial knowing they are made with AI	I feel they are less beneficial knowing they are made with AI
CJ	69.2	7.7	23.1
FAM	73.5	13.2	13.2
COM	71.3	8.3	20.4

As new learning tools based on AI technology are developed, continuing to monitor student perception of those features is key to determining satisfaction. In the survey answered by students across all three courses, students responded similarly to prior semesters (Van Campenhout et al., 2025b); students generally thought doing practice while reading was beneficial for learning, and a similar proportion of students thought these AI-generated questions were helpful for learning. When asked generally about their comfort level/trust of AI tools, the responses formed a roughly bell-shaped distribution, with fewer students at either extreme of comfort. When asked how often they used AI tools, most students selected seldom or sometimes. For students who do use AI, the most common use reported was for grammar, spelling, and formatting support. Only a small portion of students stated that they used AI for learning tasks such as generating more practice or explaining concepts that were confusing. These survey responses serve as a valuable reminder that despite the current widespread enthusiasm surrounding generative AI, not all students have expertise in, or even regularly make use of, these tools. It could be easy for faculty, administrators, and technology developers to amalgamate the sudden popularity of generative AI with ubiquitous use and expertise by students. But this is not yet the case. These typical university students are still novices in their own use of AI and evolving in their comfort, trust, and perceptions of these emerging AI tools.

The survey responses also revealed noteworthy insights regarding student awareness of AI involvement in question generation and feedback. Despite faculty being aware of this and a notice on AI-generated feedback in the user interface, nearly all students reported being unaware that the questions were AI-generated. Most students, once realizing questions were created with AI, felt they were as beneficial as before. A few students felt they were more beneficial, but a small proportion felt they were less beneficial than before. What's notable is there is a similar percentage of students who only found the questions only somewhat helpful in the first place; it could be that this same group who only found them somewhat helpful considered them even less so once discovering their AI origins. These responses raise issues of AI transparency and trust. In this case, the AI-generated questions have shown to be beneficial, and students found them to be helpful prior to knowing their generation status. Does ensuring students know the AI origination of the questions increase overall trust, or could that inadvertently erode the benefit of the questions by diminishing the perception of them for some students? Could some type of education on the generation method and validation research change student perception? These are avenues for further consideration and research.

Conclusion

Survey findings suggest that student usage and attitudes toward AI remains varied. While a small portion of learners appear comfortable integrating AI tools into their studies, many remain infrequent users of such technology, with the most frequent use for AI being spelling and grammar support. These findings on overall usage are consistent with those from Kim et al.'s (2025) survey of 982 university students, where 70% of students used AI tools once a week or less. It is key for those in higher education and educational technology alike to keep in mind that the open access and explosion of AI tools does not equate to ubiquitous student use or, importantly, mastery.

Notably, most students did not realize these new questions or their feedback were AI-driven. The majority of respondents indicated that learning-by-doing activities are beneficial for studying and that their perception of the questions was unchanged when they discovered they were developed with AI. However, discovering the AI origin influenced perceptions for a small portion of students, raising questions about transparency and trust. Regarding the AI questions assigned to these students, the learning science basis and efficacy research prove their effectiveness for learning, so a negative perception of AI reducing trust and use is not a desired outcome. Therefore, we recommend transparency with students not only that the questions were generated with AI, but also the learning science and efficacy research that explains both the rigor of the AI questions and their benefit for learning.

Based on these student perception findings further contextualized by similar research recently conducted, there are several recommendations for faculty to guide teaching and learning practices with AI tools. First, try to understand how often students are using AI and what they are using it for. Research has shown usage may not be as frequent as thought and most students are not using sophisticated learning strategies, but this may change over time. Knowing this information—even informally—can help shape both expectations and assignments. Second, ensure expectations for AI use for course assignments are both clear and aligned with university policies to provide maximum clarity for students. This includes AI tools used in the course and their purpose for learning, as previously mentioned. Third, as concluded in Tierney et al. (2025), students were most positive regarding AI tools that provided academic support, which aligns closely with our final recommendation that AI tools selected for classroom use be based in the learning sciences and have effectiveness research to confirm their benefits for students in natural learning contexts. In continuing to monitor student perceptions, researchers and developers can ensure that emergent generative AI capabilities support rather than alienate learners.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The authors declare that no AI or AI-assisted technologies were used to generate or refine the content of this manuscript. This is original research conducted entirely by the authors.

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