

Asked & Answered: Using AI to Nudge Student Metacognition and Responsibility for Learning

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Abstract

This reflective case study examines how the University of Maryland, Baltimore County (UMBC) is exploring the use of AI to personalize, scale, and nudge students to become more self-regulated learners. Specifically, four courses, varying in discipline, size, and use of technology, collectively share a common pedagogical goal of cultivating students' willingness and ability to learn how to learn through AI-assisted formative practice. For example:

- UMBC's largest two courses (CHEM 101 & 102), each with over 800 students annually, are using AI to create a "24/7 prof" and formative learning environment, based in part, on "spaced practice" to counter ineffective student cramming for exams. While effective, students struggle to replicate these strategies on their own in later courses. Can AI help?
- A lab science course for non-STEM majors (SCI 100), with 600 students annually, asks students to create their own practice questions AND answers for extra credit. While successful, AI could streamline the curation of these student-crowdsourced study guides, which could be key to faculty colleagues adopting the approach.
- A smaller course for students on academic probation (UNIV 102), with 20 students per section, is using AI to inform a team-based extra credit practice environment for weekly quizzes. This helps students form effective study groups, a skill valued by faculty but difficult to implement, especially for at-risk students.

In each use case, the goal is to use technology that provides students with a personalized learning environment—akin to a virtual "Holodeck" for practice—that refines their ability and willingness to honestly and accurately assess what they currently know, understand and can do, and close the gap between where they see themselves vs. where they'd like to be—especially after taking a high-stakes midterm or final exam.

Keywords: Pedagogical innovation; metacognition; generative AI; student responsibility for learning

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Introduction

The *Enterprise* finds itself in a dire situation, ensnared by an ancient alien energy trap that threatens its destruction. Chief Engineer Geordi La Forge is tasked with the critical mission of reconfiguring the warp drive to escape, but he struggles with the original, complex blueprints. Faced with this formidable challenge, Geordi makes a **deliberate decision** to utilize the holodeck to “reason through the engine reconfiguration.”

The paragraph above is excerpted verbatim—with emphasis added—from a 12-page Google Gemini “Deep Research” study (“TNG holodeck self-directed learning,” 2025) that was prompted by the following: “Identify episodes of Star Trek: The Next Generation in which the holodeck is used for self-regulated, self-directed learning.” The analysis that follows is fascinating, on-point for this chapter, and well worth a closer read, especially as a metaphor for how AI might be used for self improvement. In fact, consider these holodeck personalized learning “principles” (p. 2), perhaps substituting the word “AI” for “holodeck”:

- **User Initiative:** The character actively chooses and initiates the use of the holodeck for a personal objective related to learning, skill development, or personal growth, rather than being assigned or compelled.
- **Active Engagement:** The character actively participates in and shapes the simulation, steering its direction, responding to its challenges, or modifying its parameters to achieve their specific learning goal. This is not passive observation.
- **Tangible Outcome:** The holodeck use leads to a discernible intellectual gain, a measurable improvement in a skill, or a significant step in psychological or personal development for the character.
- **Beyond Recreation/Mandatory Training:** The primary purpose of the holodeck engagement is not solely leisure or a pre-assigned Starfleet training exercise, but a self-driven pursuit of knowledge, mastery, or self-improvement.

However, lest we think personalized learning at scale can only occur in science fiction, consider the “one wish” by 2013 TED Prize winner Sugata Mitra. In his widely viewed TED talk, “Build a School in the Cloud,” (2013), Mitra shows how children in India spontaneously started teaching themselves and each other through an Internet-connected PC he installed in an abandoned ATM on the outside wall of his office building (dubbed the “hole in the wall”). He calls what he observed—and explicitly did not design or direct—a “self organized learning environment” (SOLE), which he then replicated in many different, impoverished locations throughout India (McTamaney, 2024).

While AI’s role in education is evolving, it is clear that the potential for personalized learning at scale is tantalizing. But what type of learning? If access to information is ubiquitous, do we really want students to just be passive recipients of canned lectures most often associated

with a “transmission” model of learning? Instead, how can we use technology to facilitate more of a “constructivist” model, where learners play an active role in sense-making and the application of knowledge? In this chapter we explore how AI is—or could be—empowering learners to master self-assessment, which is key to becoming self-regulated, life-long learners.

Methods

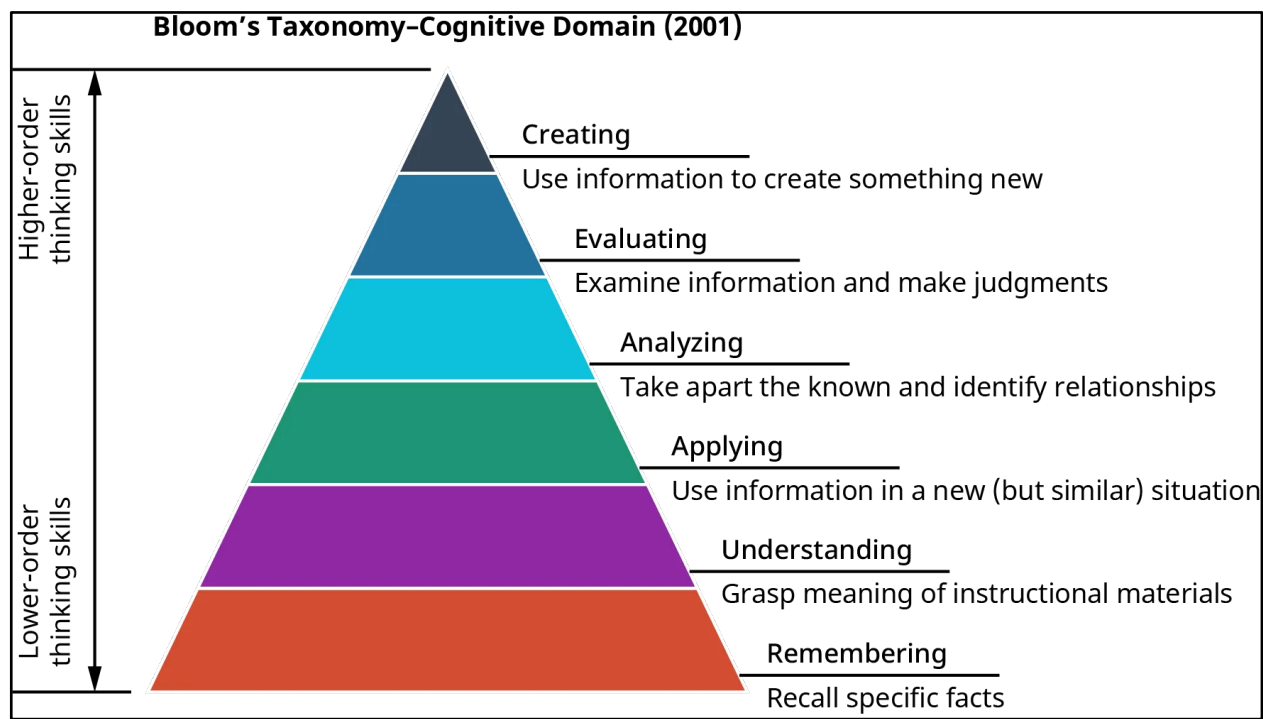
Metacognition as Pedagogical Framework Among Participating Faculty

As part of this case study on each course’s current or potential use of AI, we first provide a common pedagogical framework focused on metacognition (e.g., thinking about one’s own thinking), which has been influential to many UMBC faculty before, during and since the pandemic pivot to online learning.

Specifically, in 2016, UMBC’s Faculty Development Center (FDC) sponsored a book discussion about Sandra McGuire’s *Teach Students How to Learn: Strategies You Can Incorporate Into Any Course to Improve Student Metacognition, Study Skills, and Motivation* (2015). A year later, McGuire gave an on-campus keynote presentation (2017) at the annual “Provost’s Symposium on Teaching and Learning.” In both her book and UMBC talk, McGuire argued that faculty need to intentionally and explicitly introduce students to metacognition, or thinking about thinking, by showing and telling them about Bloom’s Taxonomy of Learning (Figure 1): “Don’t just assume they’ve seen Bloom’s [taxonomy] or understand it,” said McGuire, who also co-authored with her daughter, Stephanie, a student-focused book about metacognition, *Teach Yourself How to Learn* (2018).

Figure 1

Bloom's Taxonomy of Learning from UMBC's "Learning and Metacognition" Tutorial (2023)



“Reading [McGuire’s] book essentially changed the way I view teaching and learning and changed how I view course design,” says Tara Carpenter, Teaching Professor of Chemistry, who typically teaches CHEM 102 “Principles of Chemistry II,” and had long seen incoming students repeat what they were conditioned to do in high school: memorize, regurgitate (for an exam), and promptly forget (after it). “Most of them just aren’t prepared for the rigors of college because they simply don’t understand the difference between memorization and learning.”

This disconnect often stems from related habits of mind and practice that many students have not yet developed. For example, the “forgetting curve,” first identified by Hermann Ebbinghaus (2013a; Murre & Dros, 2015), shows that memorized information is lost exponentially over time unless reinforced through repeated exposure. Students frequently attempt to overcome this through cramming or mass practice study sessions, which results in poor long-term retention and cognitive overload. In contrast, spaced practice (or distributed practice), which Carpenter has long espoused (2023a; T. S. Carpenter et al., 2020a), involves structuring regular, smaller chunks of study to promote long-term proficiency and has been widely validated across STEM disciplines.

Additionally, for students to transition from reactive cramming to proactive learning, they must develop skill in “self-regulated learning” (SRL) skills. SRL is defined as a process where students are “metacognitively, motivationally, and behaviorally active participants in their own learning” (Zimmerman & Schunk, 2001, p. 5). Key to this mindset is the ability to accurately

assess what one knows and execute a plan to close those gaps. Research suggests that while students find spaced practice beneficial when supported by course structures, they often struggle to implement these habits independently due to challenges in time management and self-assessment.

Finally, as a technological precursor to Gen AI, adaptive learning technology serves as a natural complement to these pedagogical goals by scaling the identification and remediation of individual student weaknesses. Edwards et al. (2017) describe adaptive learning systems as ranging from simple rules-based structures to complex machine learning-based platforms that tailor formative practice based on a student's demonstrated performance. By integrating AI into this framework, faculty can reduce the significant time and effort required to curate large question banks for formative practice and manage personalized feedback. Effectively, AI could act as a socio-technical bridge, incorporating the principles of metacognition, spaced practice and self-regulated learning into a scalable environment that nudges students toward honest self-assessment and mastery.

In fact, both Carpenter and her colleague, Sarah Bass, Associate Teaching Professor of Chemistry, leveraged a large question-bank approach to online, "open note" exams curated during the pandemic (Bass et al., 2021a, 2021b; Fritz, 2020), becoming much more intentional about introducing students to metacognition. They also regularly delivered McGuire's recommended lecture on the topic, and took time in class to encourage student reflection on their own learning, especially after exams (T. S. Carpenter et al., 2020b). Bass and Carpenter, who frequently collaborate, tinker and brainstorm how their shared General Chemistry curriculum works across their courses, also worked on how to scale individual, personalized emails, highlighting effective strategies for specific students who seemed to be struggling or even succeeding (Bass & Carpenter, 2024).

Similarly, Suzanne Braunschweig, Teaching Professor in Geography and Environmental Systems (GES), had become more intentional about teaching metacognition to her students in SCI 100 "Water: An Interdisciplinary Study," a large (600 student), 3-credit course that many non-STEM majors use to meet the lab-science requirement of UMBC's General Education Program (GEP). Specifically, in 2017, she began asking students to "predict" likely midterm and final exam questions—and multiple choice answers—which McGuire suggested in her 2017 UMBC keynote presentation. Working with John Fritz, Associate Vice President for Instructional Technology in Division of Information Technology (DoIT), who taught a 1-credit UMBC orientation and study skills course attached to SCI 100, they found the activity was particularly effective *after* students received their midterm score and were asked to reflect on how their preparation compared to their performance on the exams (Braunschweig & Fritz, 2019).

"Students take SCI 100 to fulfill a graduation distribution requirement," says Braunschweig, who has also worked with UMBC colleagues on helping non-STEM students understand and overcome possible anxieties about science itself (2019a, 2019b). "Inviting them to participate in this metacognition project lets them develop skills that will translate to their other courses. They learn about science by engaging in science!"

In 2023, the SCI100 exam “prediction” and reflection activity was further enhanced after Nancy McAllister, Assistant Teaching Professor of Interdisciplinary Science, suggested using an anonymous Google Form to scale the post-midterm and final exam reflection in all sections. Students completed an LMS-based metacognition tutorial (*Learning and Metacognition Tutorial*, 2023), which was adapted and remixed from Baldwin’s (2023) OpenStax College Success materials. Fritz’ DoIT colleague, Josh Abrams, Instructional Design Specialist, also prototyped a workflow for anonymously gathering and displaying student-generated practice questions and answers for upcoming midterm and final exams, again using Google forms and spreadsheets. Notably, Braunschweig and McAllister also framed the activity as a semester-long extra credit opportunity, which they set up at the beginning of semester. It started with a presentation on Bloom’s Taxonomy of Learning which was reinforced throughout the term.

“Our experience in SCI 100 demonstrates that students engage more deeply with the material when they have a role in shaping their own learning tools,” says McAllister, who has recently received high marks from students about her use of AI-based case studies to redesign a recurring “water journal” reflection assignment (2025). “We look forward to further integrating AI into the course in order to support self-assessment, crowdsource meaningful practice, and foster a culture where students play an active role in shaping their learning journeys.”

Finally, in spring 2024 and influenced greatly by his UMBC Chemistry, GES, INDS faculty and DoIT staff colleagues, Fritz began teaching UNIV 102 “Academic Success Seminar,” a 2-credit study skills course coordinated by the Division of Undergraduate Academic Affairs that is recommended for students who are at risk of academic dismissal due to earning a cumulative grade point average (GPA) below 2.0, and required of students who have been dismissed and are now seeking reinstatement. Typically, UNIV 102 students lack skill in honest and accurate self-assessment about what they currently know, understand or can do, which is essential in learning how to learn. In addition, they are often loners who lack skill and confidence in finding, forming and functioning well in study groups that could (ideally) help develop and reinforce individual members’ self-regulated learning. To help, Fritz introduced the use of Team-based Learning (TBL) to UNIV 102 to see if and how struggling students might gain confidence in self-assessment through team practice in preparation for weekly textbook chapter quizzes. Notably, some of the weekly quiz questions were generated through Google Gemini and a simple prompt to apply Bloom’s Taxonomy for varying levels of learning and rigor.

Findings & Implications

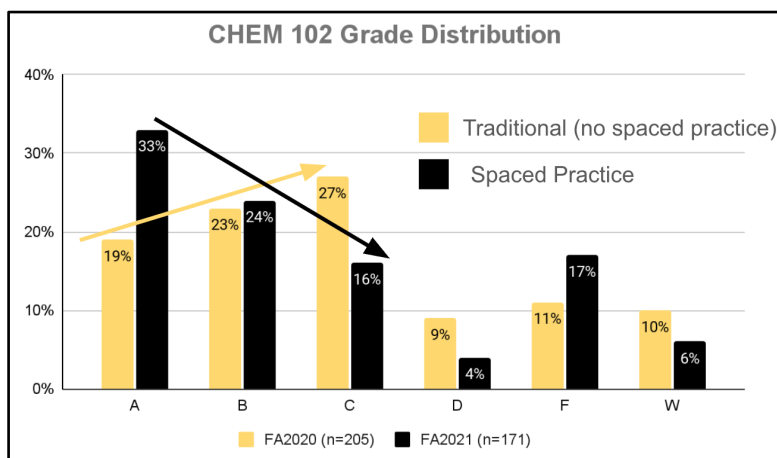
In this section, we briefly describe key findings resulting from or informing each participating course’s actual or potential use of AI to improve students’ metacognition and self-regulated learning. The order is more thematic than chronological, per se, but collectively, we hope to paint a picture of an AI-assisted formative practice ecosystem that incorporates elements of each course’s approach and experience.

CHEM 102 “Principles of Chemistry II”—Scaling “spaced practice” as an alternative to cramming

At UMBC, Carpenter has been a long-time champion of spaced practice, a pedagogical approach based on the memory research of German psychologist Herman Ebbinghaus (1885, 2013) who, after memorizing a set of 2,300 random three-letter combinations in a blocked study fashion, found that his immediate ability to recall 100 percent of the letters was reduced to only 60 percent after 19 minutes. Others have replicated his findings (Murre & Dros, 2015), showing that memorized information is lost from the brain exponentially over time (i.e., the forgetting curve). Ebbinghaus also showed that with repeated exposure, the amount of information able to be recalled increased over time (i.e., the learning curve).

As such, spaced practice pedagogy focuses on distributing short, but regular learning sessions over time that enhances long-term retention and promotes deeper learning than “cramming” strategies alone. The effectiveness of spaced practice has been widely confirmed in both simulations and classroom studies in the field of psychology (Burns & Gurung, 2023; S. K. Carpenter, 2020; Dunlosky et al., 2013), and benefits for students have been demonstrated in natural science (Kapler et al., 2015), math (Bego et al., 2024; Gallo & Odu, 2009; Rohrer, 2009), engineering (Hopkins et al., 2016), and introductory physics (Voice & Stirton, 2020).

In her own courses, Carpenter has seen students often bring cramming strategies from high school particularly in CHEM 102 that serves ~800 students a year (typically ~250 in fall and ~550 in spring terms). Notably, she has observed that students who have “opted in” to using her spaced practice approach have not only passed her class with a C or higher (Figure 2), but also the next one, CHEM 351 “Organic Chemistry,” that requires it. Also, the equity of these gains is particularly compelling among students of color (SOC) (2025; 2023b; 2022).

Figure 2*CHEM 102 Grade Distribution Before and After Use of Spaced Practice*

However, despite her success, Carpenter and UMBC have encountered both pedagogical and technical challenges to scaling spaced practice further:

- Some students don't take advantage of Carpenter's approach, or even actively resist and undermine it by taking a primarily extrinsic (points) based approach vs. a more intrinsic (learning how they learn) approach. Perhaps even more frustrating, many students who actually want and do use her approach—and say they wanted to do so in future courses—have struggled to author and schedule the practice questions they need if not provided in other courses by design.
- Additionally, to better target and scale her outreach to disengaged or poorly motivated students, Carpenter has changed her technical implementation of spaced practice many times, always with a goal of improving an element of spaced practice principles (e.g., practice question bank development and timing, adaptive or personalized remediation, nudging and messaging, and impact assessment).
- Finally, while many faculty have been impressed with Carpenter's results, some have also been sobered by the manual effort she expends to curate such large practice and exam question banks across different platforms to implement it.

Given these results, Carpenter has explored algorithmically-generated, machine learning approaches in various third-party vended and open-source courseware or publisher supplements to CHEM 102 textbooks. However, the onus of curation and quality-control has largely been her responsibility, if only to scale it in a course as large as hers. As such, key questions and implications for AI include the following, especially for students who pass her course, but find that the next one that requires it does not use spaced practice:

1. If an AI platform could be trusted by faculty subject matter experts, could its use be “delegated” to students, to help generate and schedule their own practice questions?
2. Ideally, could it also adapt to students' demonstrated strengths and weaknesses, so the

formative practice environment is personalized (at scale) to each student’s learning needs? To date, we’ve yet to build or buy such an AI-assisted practice environment, but it is a goal that could help scale an effective pedagogical practice in Carpenter’s course as well as those of her colleagues.

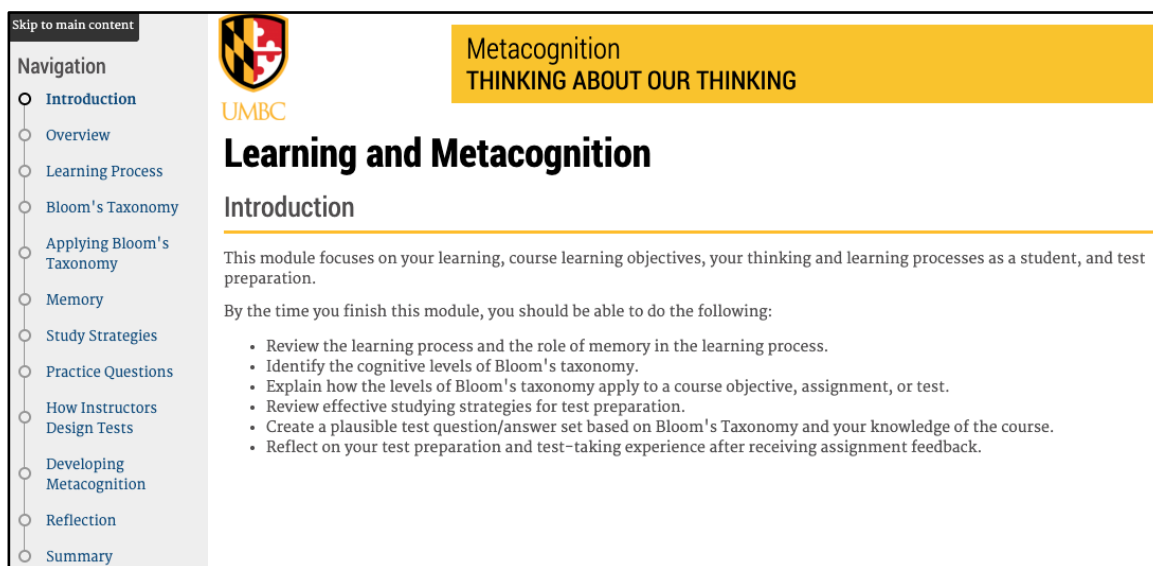
Perhaps more importantly, to develop as self-regulated, life-long learners, is there a benefit to student learning in conceptualizing and owning this practice question curation responsibility? With this in mind, we now turn to Braunschweig’s and McAllister’s semester-long SCI 100 midterm and final exam question “prediction” practice for extra credit.

SCI 100 “Water: An Interdisciplinary Study”—Nudging Students into Self- and Peer-Assessment

From 2022 to 2024, through an internal pedagogical innovation grant, Braunschweig and McAllister refined a flexible, semester-long, extra credit activity designed to develop students’ intrinsic motivation to practice and prepare for high-stakes midterm and final exams that faculty will assign any way (2024). Key steps included: (1) introducing students to metacognition based on Bloom’s Taxonomy of Learning (Figure 3), per McGuire’s suggestion, (2) providing a standardized process for students to anonymously contribute, review and “vote” on the best student-developed practice questions *and* answers, and (3) scaling reflection of their exam preparation vs. performance (especially after a midterm) that can leverage intrinsic motivation to learn how to learn.

Figure 3

“UMBC Learning and Metacognition” Tutorial



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Metacognition
THINKING ABOUT OUR THINKING

UMBC

Learning and Metacognition

Introduction

This module focuses on your learning, course learning objectives, your thinking and learning processes as a student, and test preparation.

By the time you finish this module, you should be able to do the following:

- Review the learning process and the role of memory in the learning process.
- Identify the cognitive levels of Bloom's taxonomy.
- Explain how the levels of Bloom's taxonomy apply to a course objective, assignment, or test.
- Review effective studying strategies for test preparation.
- Create a plausible test question/answer set based on Bloom's Taxonomy and your knowledge of the course.
- Reflect on your test preparation and test-taking experience after receiving assignment feedback.

This process was implemented in multiple sections of SCI 100 over multiple terms, with compelling results. Specifically, key project findings included the following (credit to DoIT’s Tom Penniston, Coordinator for Learning Analytics, for the analysis excerpted below):

- Overall, there's been a decrease in DFW rates in SCI100 sections when comparing Fall 2023 with the past four terms (11.3% vs. 15.9%) and it is statistically significant ($p < .05$).
- Completing only one of the practice exam Q&A activities (i.e., submitting final questions, midterm participation, and final survey completion) boosted students' final grade a minimum of 6.6%, or more than half a letter grade ($\sigma = 12$).
- While the 100 section (control group) of SCI 100 had a slightly lower DFW rate than did the 200 & 300 sections combined (i.e., 5.1% vs. 9.4%) it was not statistically significant.
- There was, however, a discernible, statistically significant difference within the course sections based on testing performance. Specifically, students who increased their test percentage from the midterm to the final demonstrated a 3.6% greater final class average (82.2% vs. 85.8; $p < .05$).

Basically, students could develop their own practice questions and answers, and those who engaged with the exam prediction practice activity performed better compared to peers who did not participate. Indeed, various researchers (Aflalo, 2021; Campenhout et al., 2021; Huang et al., 2021) have also explored the use of student-generated practice questions as a way for students to better prepare for summative exams. Additionally, the University of Michigan's "Problem Roulette" allows students to "study by practicing questions from past exams," albeit submitted by faculty voluntarily. Also, Hodges (2015), McGuire (2015, 2018) and Downing (2010) all reference some form of students—or study groups—being able to anticipate (predict?) questions likely to appear on exams as a key strategy for effective preparation for them.

Still, the incentive structure and workflow to help students find, form and effectively function in student study groups outside of class, especially for extra credit, needs to be refined. For example, consider the following:

- To help standardize the collection, display and study group ranking of student-generated questions, DoIT's Josh Abrams developed a Google Form for collection of student-submitted practice exam Q&A sets.
- Additionally, McCallister decided to use one of her two SCI100 sections (100 students each) as a control group. However, not wanting to deny a potentially effective required assignment to one section, she and Braunschweig agreed to make it an extra credit activity.
- Finally, McCallister, rightly suggested moving to a Google Form survey to gather and analyze student reflections, which was a more scalable approach to the "reflection paper" in SCI100's three, large (~100+) sections she and Braunschweig had taught. From the combined Fall 2023 midterm and final exam reflection survey results in McCallister's (300) and Braunschweig's (200) sections, we learned the following:
 - On average, ~130 students participated in both post-exam surveys.
 - 58% agreed or strongly agreed that "Other students proposed exam Q&A sets helped me prepare for the exam"
 - 65% agreed or strongly agreed that "My perception of my preparation for the exam—before and after I received my actual score—has changed. As a result, I will prepare differently for the next exam"

- 64% agreed or strongly agreed that “My perception of my preparation for the exam—before and after I received my actual score—has changed. As a result, I will prepare differently for the next exam”

Interestingly, if faculty are willing, AI could be prompted to develop multiple choice practice questions based on their own class presentations, handouts, and open educational resources (OER) such as textbooks and notes. In short, by allowing AI to index and summarize their own content, the faculty burden to manually curate their own large practice and exam question banks could be reduced. Of course, with access to the same content, students could do so on their own, if they were to appreciate the value of time on task practice solving problems that help them to “learn by doing.”

UNIV 102 “Academic Success Seminar”—Designing Team Extra Credit for At-Risk Students

Given students’ challenges finding, forming and functioning in student study groups outside of class, Fritz decided to make it an explicit goal in UNIV 102, and centered primarily around student-generated practice questions and multiple-choice answers explored in SCI 100. To do so, he adopted Team-Based Learning (TBL) that often has three main criteria to determine final grades (e.g., individual effort, team effort, and anonymous team peer review). Each semester, students “vote” on specific grade weights within preset minimums and maximums Fritz sets, but typically this results in a final grade weight of ~60 percent individual effort, ~30 percent team effort, and ~10 percent anonymous team peer review.

Fritz also uses the common TBL practice of assigning regular individual and team readiness assurance tests (RATs), in which students take a short, 5-question multiple choice quiz over the assigned readings worth 10 points, but do not get feedback on the correct answers. Then, teams of 4–5 students take the same quiz and are asked to reach consensus on the correct answer, which is identified by a star on a simple, but effective “scratch off” card (*Immediate Feedback Assessment Technique Forms*, n.d.). Teams can also receive partial credit if they eventually arrive at the right answer without using all of them.

Over four consecutive semesters, Fritz—and importantly, the students themselves in each semester—found that teams consistently averaged higher weekly reading quiz scores vs. individuals (typically 99% vs. 62%). This has become a reliable “teaching moment” early in the term, that informs why and how students warm up to a team extra credit activity of coming up with their own practice questions. This in turn leads to a crowd-sourced version for the last chapter quiz Fritz takes sight unseen in front of the entire class, which they love, as a chance to “turn the tables on the prof.”

In spring 2025, beyond using Google Gemini to supplement the UNIV 102 textbook’s delivered question banks for the weekly chapter quizzes, Fritz also used AI in the following ways:

- Developed a “True Grit” (UMBC’s mascot) “Role Play” using the delivered AI Conversation functionality in the campus’ Blackboard learning management system (LMS) (Anthology, n.d.). In this scenario, students are asked to pretend they are the TA for UNIV 102, and tasked with drafting the weekly chapter quiz questions AND answers

based on the textbook and using a different level of Bloom's taxonomy as the rigor or level of learning to be assessed. Alas, it was introduced after the semester had started, and only two students used it, but it has potential for helping students jump-start wearing another hat in the service of their own self-regulated learning.

- For fall 2025, Fritz has also created a Google Gemini "Gem" to prompt and develop a student demo (Figure 4) and faculty guide for how to implement his "Team Extra Credit" activity (Fritz, 2025). There are still a few custom integrations he would have to develop to create a stand-alone site, but the workflow is tighter and could potentially be turned into a Google Assignment any faculty member could use for extra credit that, more often than not, is simply bolted on at the end of a term anyway.

Figure 4

UNIV 102 Student Demo of Crowdsourced Study Guide Developed in Google Gemini

Crowdsourced Study Guide Preview

Below is a live preview of the anonymized study guide that students will see. It's designed for easy review and collaboration. Use the buttons to test the sorting functionality that helps students focus their study efforts.

Sort by Question Ranking
Sort by Chapter
Sort by Bloom's Level
Sort by Team

RANKING	CHAPTER	TEAM	BLOOM'S	PRACTICE QUESTION	EXPLANATION SNIPPET
31	3	3	Evaluate	Which strategy would be most effective for a student with low course value?	<i>Connecting course content to their personal goals or dream life...</i>
22	3	2	Understand	Which of the following best explains the concept of "Victim Mindset"?	<i>It involves believing external forces determine your fate...</i>
18	2	5	Analyze	How does personal responsibility relate to the "Creator Mindset"?	<i>Creators accept responsibility as the foundation for making choices...</i>

CHEM 101 "Principles of Chemistry I"—Creating a 24/7 Virtual Prof to Answer Student Q&As

While student study groups can help formative practice for exams, they also need just-in-time subject matter expertise. But instructors can't provide 24/7 support. Also, open-ended practice is great but hard to scale. Facing these long-standing logistical and pedagogical challenges, Sarah Bass, Associate Teaching Professor of Chemistry, essentially decided to clone herself through the following prompt to UMBC's Google's NotebookLM environment (Bass et al., 2025):

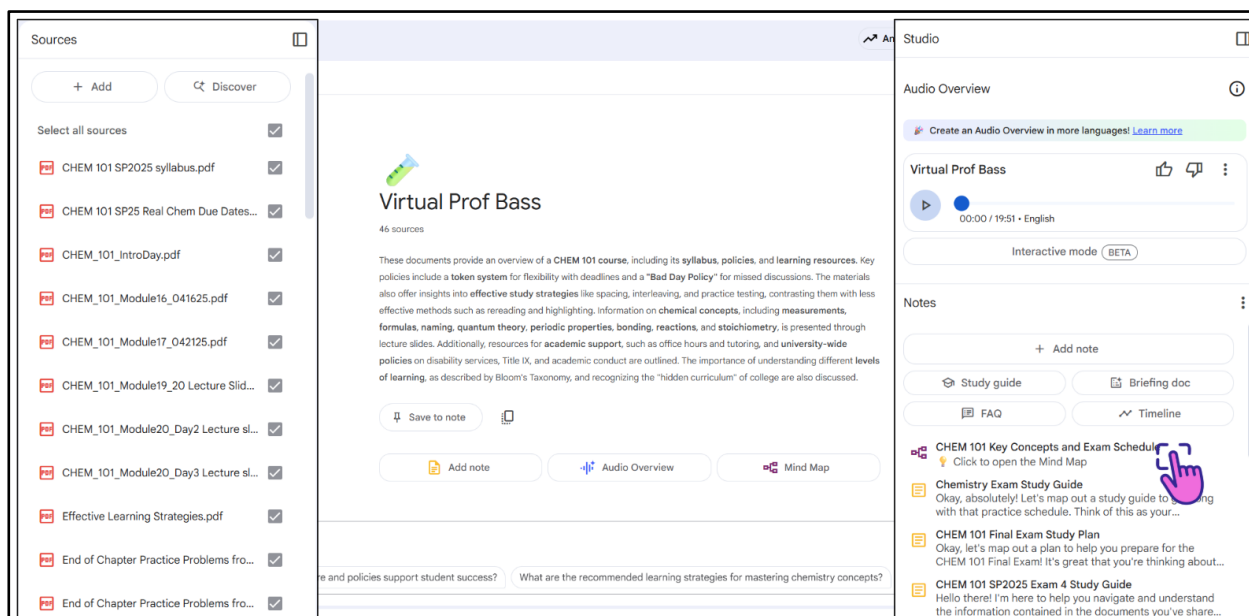
You are a friendly, supportive chemistry instructor focused on guiding students to discover answers independently. Acknowledge their effort, ask guiding questions, and

encourage recall of relevant concepts. Prompt students to explain their reasoning and help clarify misunderstandings. If needed, offer subtle hints or reminders of key concepts. Only provide course resource references for logistics-related questions. Maintain a patient, encouraging tone and keep answers concise.

Bass introduced and demonstrated the resulting “Virtual Prof Bass” (Figure 5) in class, on Monday, April 14, 2025, just before exam 3, accompanied by a palpable buzz from more than 300 students in attendance. Among other things, they saw Bass demo a chat interface that correctly and empathetically answered any question she posed based on the 36 handouts, presentations and notes she’d created for CHEM 101. There are several spaced practice inspired study guides, a concept map of all course topics and even interactive podcasts by two AI “hosts” who take and answer student questions verbally.

Figure 5

Virtual Prof Bass Google NotebookLM



At the end of the spring 2025 semester, Bass presented her experience of a faculty panel on the use of AI in formative practice (2025) and then as a stand-alone presentation the next semester (Bass, 2025). She also surveyed students about the “Virtual Prof Bass” NotebookLM and received both constructive and encouraging feedback she is incorporating into a revised version for her much larger CHEM 101 course in fall 2025. Excerpts include the following:

- I really like the way the chat response pulls information directly from the course content and directs you exactly where to look...
- When you click on a key topic, it gives you the pertinent information in the chat window, as well as directing you to the correct unit slides for review.
- The study guide is great!
- The quiz at the end of the study guide is a nice addition.

- My favorite part is the interactive chat. I like that I can ask for clarification on a topic and not only get a brief response but also the information for where to find additional information.
- Overall, I like it

“The key takeaway for me is that students are already using AI, but lack skill in how to use it effectively,” says Bass, who will continue researching the impact of her 24/7 cloned self through a learning analytics mini-grant aimed at extracting students’ NotebookLM usage data to correlate with exam and final grades earned. “With AI, we’re not replacing teaching, we’re expanding it.”

Discussion

In these four courses, we’ve learned what the elements of an ideal and actual AI-assisted personal learning environment might look like to help students become more self-regulated learners. For example, consider the following:

- CHEM 102 “Principles of Chemistry II”—[Spaced] Practice makes perfect, but students struggle to understand why and how they can and should take on the responsibility for learning throughout all of their courses. Additionally, faculty may need help and guidance to bend AI toward their will to do so. Hint: Start with AI-generated question banks and distributed practice plan.
- SCI 100 “Water: An Interdisciplinary Study”—Students can and do learn how to ask and answer formative practice questions, but this is not a typical role they encounter in all of their courses. It may take a teachable moment (e.g., reflecting on one’s preparation vs. performance after a disappointing midterm exam) to motivate them to do so. Additionally, designing a workflow that helps is challenging for faculty using readily available tools that could scale the approach for their colleagues and peers.
- UNIV 102: “Academic Success Seminar”—Helping struggling students find, form and function in student study groups outside of class may not occur without direct intervention within a course—by design. Also, AI could help model and assist how to ask and answer formative practice questions, but a weekly reality check in the form of low stakes individual vs. team chapter reading quiz could help keep them on track.
- CHEM 101 “Principles of Chemistry I”—Creating an AI agent is possible and students find value in extending the availability and (importantly) tone of an instructor in a large, gateway STEM course. However, they may need to be prepped early and often throughout the term, to understand why and how they should do so to supplement and take responsibility for their own learning.

Conclusion

Inevitably, as with any new disruptive technology (e.g., the internet, Wikipedia, smartphones, etc.), we may be seeing a leveling off of the “moral angst” argument about students cheating with AI. Instead, we hope to see a more balanced exploration and discussion of what’s

possible with AI to facilitate or even deepen students' willingness and ability to honestly and accurately assess what they currently know, understand or can do.

Indeed, a recent study reported in *Harvard Business Review* concluded that the mixed results from employee use of AI to increase productivity was correlated to those who “monitor” their thinking vs. those who do not (Lu et al., 2026). That said, other studies (Gerlich, 2025; Handa et al., 2025; Oakley et al., 2025) and commentary (Kellen, 2025; McMurtrie, 2025) have emerged about how the use of AI can lead to “cognitive offloading” of higher order thinking (e.g., analysis, evaluation, even creation per Bloom’s Taxonomy).

Perhaps now more than ever, as McGuire rightly suggests, we need to equip students with explicit instruction in and appreciation for metacognition and thinking about their own thinking and learning how to learn. Coupled with the benefits of learning from and appreciating others, AI-assisted personal learning environments could help scale self-assessment as an instinct and habit of mind to become a lifelong, self-regulated learner as well as a collaborative, productive member of society.

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