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Generative AI in Asynchronous Education: A Comparative Study of Student Engagement and Learning Outcomes

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I. Introduction

As higher education increasingly embraces flexible, technology-enhanced learning, understanding how different instructional formats affect engagement and learning is essential. Asynchronous courses--which have existed as correspondence courses since the early 1900s and expanded with the advent of information technology in the 1990s [1]--became a new norm in higher education during the social isolation of the coronavirus pandemic. Asynchronous learning allows students to engage more ubiquitously as fits into their schedules [2] and offers alternatives to in-person learning that are cost-effective for all stakeholders [3, 4]. With widespread, rapid, amateur adoption of asynchronous teaching, many faculty were introduced to both the potential benefits and challenges involved in leveraging online teaching and learning modalities.

While asynchronous courses provide accessibility and self-paced learning, they often struggle with reduced interaction and feedback compared to in-person settings [5]. Attrition is more pronounced in asynchronous courses [6], with 10%-20% higher dropout rates nationally compared to in-person courses [7, 8]. Student engagement plays a moderating role in their learning in blended and asynchronous modalities, making it particularly important to support [9]. Many studies have confirmed that students' intrinsic motivation impacts their engagement in online course activities and the importance of that engagement for student learning [10].

Targeting students' engagement therefore requires course designs to intentionally focus on building and sustaining students' motivation. Integrating AI into asynchronous courses may offer a way to bridge engagement gaps through adaptive feedback and real-time scaffolding. The current generation of learning technology can address motivation. A recent systematic literature review of AI-assisted asynchronous learning identified 24 rigorous studies [11]. Among the six key applications of AI leveraged in these studies, some may be prohibitively costly for faculty to easily implement, such as affording the equipment and training to use voice recognition and eye-tracking technology or amassing sufficient data to use machine learning for data analysis to inform course design.

This study compares two offerings of the same Cryptography and Data Security course—one taught asynchronously online and another taught synchronously in-person —to examine how Generative AI/LLM tools influenced engagement, creativity, and development of content knowledge. The course uses an application suggested by [11]'s review, AI-powered bots in smart learning environments, combined with project-based learning. The comparison provides evidence-based insights into how AI can enhance learning to inform future online and hybrid course designs in cybersecurity education.

II. Course Design and Activities

The asynchronous Cryptography and Data Security course is redesigned around three structured phases—Priming, Discussions and Design, and Synthesis—with Generative AI/LLM tools integrated throughout each phase.

Phase 1: Priming. Students engage with course materials (e.g., short videos of the instructor lecturing, readings, examples of concepts in practice) on their own schedule while AI supports comprehension and connections. These activities are intended to improve engagement by making them flexible around student learning needs, but without sacrificing rigorous expectations or conceptual depth. The course policy for engaging AI tools during this phase encouraged students to use a Virtual Learning Assistant when they find themselves with gaps in their background knowledge or questions about the content.

Phase 2: Discussions and Design. Students use AI to brainstorm creative projects, address challenges, and participate in peer-led forums. The goal of this phase is to deepen students' understanding of course concepts by allowing them to apply their knowledge in a hands-on setting. Students are divided into groups, with each group responsible for developing a project on an assigned topic. For each project cycle, one group serves as the designers while the remaining students act as attackers who critically evaluate and challenge the presented solution.

Phase 3: Synthesis. Students evaluate project strengths and weaknesses, prepare reports, and reflect on their process with LLM-based tools. The goal of this final set of activities is to strengthen student retention of their learning while practicing professional-quality communication and documentation skills.

By integrating opportunities for ethical AI use, fostering creative problem-solving, and supporting more dynamic student interaction, the updated asynchronous setting aims to prepare students more effectively for the complex challenges of modern engineering practice. More details on the implementation of this cycle in this asynchronous course are available in a second paper at ASEE.

In contrast, the in-person offering of the course followed a traditional lecture-based structure with structured in-class discussions and hands-on assignments. The three-phase learning cycle was not implemented in this setting, as its Priming and Discussion–Reflection phases require sustained out-of-class engagement and asynchronous interaction that are incompatible with the fixed temporal constraints of in-person instruction. To avoid confounding instructional modality with pedagogical structure and to preserve internal validity, the in-person course retained its established format and incorporated only a representative project adapted from the asynchronous offering to assess limited transferability. Consequently, the asynchronous course served as the sole experimental environment for evaluating the three-phase learning cycle, while the in-person offering functioned as a controlled comparative baseline.

III. Research Methods

This study uses a comparative case study design to assess whether and how an asynchronous course design can be leveraged to improve student engagement and learning. The two cases--one section offered asynchronously through a series of virtual assignments and the other section representing a more traditional, synchronous in-person class modality--are each explored and compared to each other to address the following research questions:

RQ1. To what extent were students equally engaged across the synchronous and asynchronous course sections?

RQ2. To what extent did students achieve the learning objectives of the course across modalities?

RQ3. To what did students attribute their engagement and learning in each of the course sections? To what extent did their experiences align with the theory of action in the course design for the asynchronous section?

A. Participants

The study involves two course sections of the same class, Cryptography and Data Security, taught at the same university by the same faculty member. The university is a private, STEM-focused institution located in the Northeast U.S. The instructor has taught the course approximately 9 times at the graduate level and 9 times at the undergraduate level in their 10 years as a faculty member.

A total of 48 undergraduate students were invited to participate in this study - 14 enrolled in an asynchronous online course section and 35 enrolled in a synchronous in-person course section. In the synchronous section, 100% of students participated in full data collection (including the survey); 67% of students in the asynchronous section completed data collection.

B. Data Collection

Assessment of student learning in the two Cryptography and Data Security course offerings used multiple methods, including AI interaction logs, project rubrics, peer engagement measures, and self-reflections. The Student Assessment of their Learning Gains (SALG), a post-only validated survey constructed with support from the NSF as an alternative to course evaluations, was administered at the conclusion of both courses [12, 13] (see Appendix A). Student writing assignments that required they explain how they used LLM-based tools and their interaction links (which show what they asked and the LLM’s responses) were also collected.

C. Analysis

Data was organized into three categories aligned with the research questions: evidence about student engagement, evidence about student learning, and evidence about learning activities' influence on student learning. After data cleaning and organizing the dataset, quantitative data were assessed for assumptions of comparative statistical analyses. Due to the small sample size, non-parametric tests were chosen as the most appropriate and Mann-Whitney U tests were conducted to compare rank ordering, rather than comparing means through independent samples t-tests. These procedures allow us to appropriately detect statistical significance with a small sample size; however, there remains a heightened chance of type 2 error in which meaningful relationships are not detectable in such a limited sample. This leads to the necessity of interpreting any lack of significance cautiously, while allowing us to interpret the detection of statistical significance within the dataset. A significance level of $p = .05$ was set.

Qualitative data were thematically coded using iterative rounds using the constant-comparative method [14]. Author B served as the primary coder with Author A serving as a peer debriefer, a strategy supporting the credibility of the resulting themes [15].

IV. Findings

A. Student Engagement

Student engagement is generally considered to have three components: behavioral engagement, cognitive engagement, and emotional engagement [16]. In terms of behavioral engagement, both sections experienced high degrees of retention: 93% of students in the asynchronous section completed the course successfully as did 94% of students in the synchronous section. These retention rates are typical of the university where students are generally high-achieving and students will often choose to retake a course rather than receive a grade that lowers their GPA. While class attendance was intentionally not tracked in the synchronous section, the class was regularly attended, either live or by viewing the course lectures, which were recorded and shared for online viewing. Students in both modalities completed all of the assignments.

Cognitive engagement was observed in how students interacted with each other and with the instructor during learning activities. For example, in the in-person section, the project assignment relied on an understanding of sponge type hash functions, which was discussed in class during Week 4. In addition to the opportunity to ask questions of each other and of the instructor during the synchronous class meeting, students also viewed the recorded class session more than 50 times; given the number of students in the course, this means that at least some subset of students viewed the course content multiple times. This suggests that students had engaged in the project assignment sufficiently to have determined that this content was critical to it and engaged in the learning activities they needed to be successful. In the asynchronous section, cognitive engagement was observed in the depth of student work submitted as attacks on their peers' submitted cybersecurity designs.

Emotional engagement was assessed largely in terms of gains in self-efficacy, as measured in the end of term survey in both sections. Two survey items asked students as a result of their work in this class what gains they made in confidence that they understand the material and in confidence that they can do cybersecurity work. Mann-Whitney U tests confirmed that there were no significant differences in students responses to these measures of self-efficacy across the two sections. The medians for in-person students (Mdn = 4, IQR = 4-5 and Mdn = 4, IQR = 3-5, respectively) were not significantly different from the medians for asynchronous students (Mdn = 4, IQR = 2.5-4 and Mdn = 3, IQR = 2-4), U = 181, p = .21 and U = 174.5, p = .08, respectively.

In conclusion, the AI-supported asynchronous modality was able to achieve similar levels of student engagement as the in-person version of the course.

B. Student Learning Outcomes

Survey data revealed comparable conceptual understanding of the technical core of the course between groups. There were no significant differences in the first three student learning objectives related to this technical content knowledge (see Table X), which assessed students' understanding of block ciphers, message authentication codes, public key encryption, digital signatures and key establishment. Students also reported similar development of professional skills in the online course as they did in the in-person classroom, with no significant differences in learning how to give and receive feedback, professional writing, or collaboration skills (see Table X).

Table X. Mann-Whitney U Tests Comparing Student Learning Outcomes Across Modalities
[INSERT HERE]

There were some areas in which students in the asynchronous section and those learning together in-person exhibited different learning outcomes. These patterns largely fit our expectations for each modality. Students in the in-person section showed stronger conceptual coherence, reporting greater gains in their understanding of the main concepts explored in the class and the relationships between the main concepts, as well as increasing their comfort level in working with complex ideas (see Table X).

Students in the asynchronous section produced projects that demonstrated higher creativity and analytical depth. Interestingly, students in the in-person section reported stronger gains in understanding how studying this subject area helps people address real world issues than those in the asynchronous section (see Table X). However, student projects in the online section demonstrated greater levels of transference of ideas explored in the course to addressing new real-world cybersecurity designs. This may suggest differences in students' self-awareness of their learning or may reflect slight differences in the measures: understanding and doing are different skills, which is central to the theory of action behind redesigning the asynchronous modality's learning activities to focus on more active learning than typically used online.

C. Activities Supporting Engagement & Learning

Overall, the findings suggest that Generative AI/LLM integration can enhance engagement in asynchronous formats while maintaining comparable learning outcomes as in-person courses. Students in the asynchronous section used AI tools to clarify complex concepts and generate creative ideas through project-based learning and engaged in deeply reflective discussions. There were, however, three major differences in what students indicated supported their learning most across the two modalities.

Mann-Whitney U tests were conducted to assess how comparable student experiences of learning activities were in supporting their learning across the asynchronous and in-person versions of the course. Students in the in-person section reported that the high-level overviews of the modules were significantly more helpful to their learning than students in the asynchronous section (see Table X). This aligns with the findings that in-person students demonstrated greater conceptual connections across the main topics of the course than those who took the course asynchronously.

Table X. Mann-Whitney U Tests Comparing Gains from Student Learning Activities Across Modalities

[INSERT HERE]

Class discussions looked different across modalities, though both reflected high degrees of engaging in the class. Students in the in-person section could ask questions during class periods to prompt discussion not only with the instructor, but also with their peers in the class. Because class sessions were posted online, students who did not attend the session could also benefit from the conversations. However, students in the in-person section still reported that they gained significantly more from both participating in and listening to the discussions during class (see Table X).

Students in the asynchronous section, on the other hand, reported learning more from questions asked by students during their presentations than those in the in-person section (see Table X). This may be related to interpreting the question to reference sessions where students would attack the asynchronous students' presented cybersecurity solutions and question their design - a learning opportunity not available to students in the in-person section who only experienced student questions during their project presentations at the end of the course.

Finally, students in the asynchronous section reported that using LLM-based tools helped their learning significantly more than students in the in-person section (see Table X). Several of these students noted that they benefited from using the LLM-based tools as a virtual tutor. One student in the online section noted, “I ended up using copilot and gemini quite a bit during the course. It was quite helpful to get me to wrap my head around things.” Another shared that LLM-based tools “greatly helped to walk through concepts from course material and explain both high-level and low-level algorithm steps.” These conceptual benefits were described as being more useful than traditional search engine tools. As one student stated, “[LLM-based tools] help summarize and provide an overview of the problem. Save time and straightforward to the problem instead of general answer and spend long time searching, looking each resource when doing google search.”

Although these were the most common descriptions of how students in the asynchronous section described their use of the LLM-based tools, there were two additional ways of leveraging them that were shared by students. In addition to increasing efficiency in terms of finding information available on the web, one student used an LLM-based tool to help increase the efficiency of assessing repos in Github. Being able to more quickly and systematically analyze repos allowed them to be more ambitious in their work within the time available to them.

Another student noted that they positioned an LLM-based tool as an accountability buddy:

> Using a Virtual Learning Assistant was helpful as I would have it create broad/rough outlines of the work that needed to be done so that I wouldn’t stray away from the professor’s intentions as I do tend to go down research pits where I spend a lot of time researching a subject and then not be able to use the information learned.

This represents a novel aspect of the efficiency function originally intended in embedding LLM-based tools into the asynchronous course. In all three types of uses, students in the online section used LLM-based tools to greater effect than students in the in-person section. All students had access to copilot and gemini, but the in-person students were not instructed in how to intentionally leverage them.

Only one in-person student reported using generative AI and LLM-based tools similarly to those in the asynchronous section. This student described the following:

Whenever I encounter a concept that is unclear or difficult to understand, I rely on the assistant to clarify it and provide additional explanations. For example, when I struggled to understand certain security concepts in my coursework, the Virtual Learning Assistant broke them down step-by-step and offered examples that made the material much easier to grasp.

In contrast, several students noted that the limitations of these tools. One student shared that,

> Using a Virtual Learning Assistant definitely accelerated the process of creating code, etc. but it also highly decreased the depth of understand complex topics. Example: Implementing a particular algorithm is too easy using AI. You don't actually learn programming from just prompting an AI.

In fact, one in-person student's description of their reluctance to rely on these tools hit upon the reason for being more intentional in the way they were taught to asynchronous students. While describing their assessment of the pros and cons of using such tools, this in-person student indicated,

> For general concepts it can be very powerful for summarizing or being a search engine capable of parsing unrefined human ideas to more refined searches. However, for detailed explanations/questions about concepts it can be a hit or miss. Because it is only as good as the information it pulls from, it can be wrong often.

This student and their peers in the in-person section have learned enough about this risk associated with unfiltered generative AI tools like copilot and gemini. Students in the asynchronous course, by contrast, had access to generative AI and LLM-based tools deployed using a RAG unit for quality control. By introducing this concept and teaching students about the way it would improve the information they would receive through the Virtual Learning Assistant, this perspective was curtailed.

V. Discussion

A. Implications

Asynchronous learning has been studied in digital design, cognitive network design, and mathematics courses within computer engineering departments [17]. This study extends this research into the context of cybersecurity. The findings that demonstrate the impact of the asynchronous section was similar to that of the in-person section suggests that this is a promising modality--when done intentionally and with sufficient attention to high-impact practices.

Though piloted in cybersecurity, this three-step model is broadly transferable across disciplines, offering a scalable framework for reimagining asynchronous learning with AI-supported scaffolding, peer interaction, and creativity. As in other emerging scholarship of teaching and learning [18], the findings of this case study suggest that AI tools can enhance how well cybersecurity students learn to transfer theoretical knowledge into novel practical applications. This transferability is a critical skill in cybersecurity; the three-step model described here offers opportunities to practice this skill within the context of student autonomy and authentic problems rarely offered in more teacher-centered courses.

One of the most pervasive barriers to getting faculty to change how they teach courses is the time involved, which detracts from the time available for research and dissemination that is critical for career advancement [19]. As Børte, Nesje, and Lillejord [20] frame it, the what of college teaching may constantly be evolving, but the how of college teaching is incredibly stable. It is not sufficient for research to demonstrate that redesigning courses leads to stronger student outcomes; there must be attention paid to whether the strategies suggested as pragmatic enough to be attractive to other faculty. The start-up costs of redesigning the course in this case were modest, though not insignificant. Author A estimates that the course required approximately five hours for video recording and two hours of editing for each three hours of class.

Compared to faculty in other disciplines, however, academics in cybersecurity are relatively well-positioned to know how to use and set up AI learning tools without requiring much training. Much of the existing tension in higher education around leveraging AI to reach the scale and access afforded through asynchronous courses has been beyond this discipline, where a certain level of technical unfamiliarity influences faculty perspectives and teaching practices. In this sense, faculty in cybersecurity could be positioned as teaching mentors for those who are hoping to focus on student-centered teaching and learning with the assistance of LLM-based tools.

B. Limitations

This scholarship of teaching and learning offers an early examination of an issue critical to educational practice; the study design has several limitations that prohibit us from generalizing the findings. The sample size is small, limited to students at a single university, and taught by a single instructor. The methodology used does not provide sufficient range in sampling at any of these levels to extend the findings beyond the sample. The lack of a true experiment design with random assignment to the asynchronous and in-person modalities also confounds the findings. There is likely to be bias in which students self-select into each modality that are accounted for within the analyses.

C. Future Directions

Discovering universal paradigms and best practices is not the aim of scholarship of teaching and learning. Rather, this study—and others like it—are intended to surface promising practices. The evidence here is gathered to give direction to future curricular and instructional practices, as well as to justify time and resources on more extensive research.

Future iterations of the asynchronous course might encourage students to use the Virtual Learning Assistant more specifically for making conceptual connections. Students tended to use this AI tool only when they hit a stumbling block or to address a technical problem they faced.

Instruction in the beginning of the course could more explicitly demonstrate to students how they can use AI to test their knowledge of various threshold concepts. Examples of prompt engineering tactics to maximize how the Virtual Learning Assistant can be used to direct feedback from the AI tool could mimic the way an instructor might notice trends in conceptual gaps in live discussions in an in-person setting. This would extend the ways in which students utilize the Virtual Learning Assistant as a virtual tutor by redirecting that tutoring towards conceptual connections.

A second set of changes might also be added later in the course to prompt students to remember to utilize the Virtual Learning Assistant in this way. Assignments that ask students to note in their VLA logs where they engaged in this kind of assistance and that require the students to reflect on what they learned as a result could serve as both reminders and to solidify their learning gains.

Additional analyses might compare this course with asynchronous courses that do not integrate AI. Comparing implementation, student experiences, and learning outcomes across This would require that an additional section covering the same curricular content that is not utilizing AI tools be identified, which is currently not available at the university.

A larger study that leverages partnerships across university settings might also allow for an increased sample size and variability of institutional contexts to allow for more sophisticated analyses. Generalizability will be difficult, if not impossible, to achieve as the ethics involved in assigning students to specific course conditions rather than allowing for self-selection largely precludes universities from allowing for such practices. However, even with self-selection bias, a larger sample would allow for multilevel statistical models that could account for these influences on learning outcomes.

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