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Exploring Student Perceptions of Working with Generative AI in Agent-Based Modeling

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Abstract

Generative artificial intelligence (AI) tools are rapidly reshaping how students engage with biomedical engineering coursework, yet their impact on conceptual understanding and technical skill development remains poorly understood. In this study, we investigate how students use AI to construct and refine an agent-based model (ABM). In an ABM, biological systems are represented through rule-based interactions derived from scientific literature and translated into code. The ABM building process provides a unique testcase for AI because it requires a baseline understanding of a biological system and the technical skills to implement the model in code.

To understand how students use AI, we employed a parallel mixed-methods approach in a combined undergraduate and graduate biomedical engineering course at a large R1 institution. Thirty-four students (27 undergraduate, 7 Ph.D.) were placed in groups and tasked with developing an ABM of a biological system of their choosing. Students then independently engaged with AI by prompting it to generate and revise their model code based on their model rules. Students completed pre- and post-course surveys that assessed their AI use and perceptions along with a written reflection about their experience using AI.

Students generally reported some advantage to using AI to develop their ABM. AI tools helped students understand the system they were modeling and the fundamental principles of constructing an ABM. Students who frequently used AI for other classes and assignments reported greater proficiency with AI tools, but this was accompanied by increased feelings of dependence on AI. Many students also noted a clear disconnect between the model AI described encoding and the actual code syntax and output. Overall, these data suggest that while AI can support student learning, there could be an advantage to teaching targeted use of AI as a tool for specific contexts to students in the classroom.

Introduction

Generative artificial intelligence (AI) tools such as ChatGPT and Claude are changing the way students engage in coursework in the biomedical engineering classroom. Biomedical engineering is the engineering discipline that most closely intersects with medicine and healthcare, which is one of the fields most quickly adopting AI in day-to-day activities [1], [2]. From AI notetakers to AI diagnostic tools, AI tools have a prominent role in healthcare. Therefore, it is essential for biomedical engineers to have domain knowledge of AI. AI literacy is going to be a key identifier in future hiring practices, and based on the current trajectory, teaching students to reject the use of AI will not equip them for future career success.

The rapid evolution of generative AI tools has outpaced the collective understanding of how these tools influence students' comprehension of course material and learning of distinct technical skills [3], [4], [5]. Additionally, there is growing concern over the use of AI in the classroom. Faculty and students hold varying, and sometimes conflicting, views on the pedagogical value of AI tools and whether it enhances or undermines problem-solving skill development. The evolution of AI is inevitable, and there is a pressing need for research that informs how instructors can intentionally and effectively incorporate AI to support student learning.

In this study, we investigate students' perspectives on their use of AI in a course that teaches a type of computational modeling called agent-based modeling. Throughout this paper, we will use the term "AI" to specifically refer to generative artificial intelligence tools, including large language models (LLMs). In an agent-based model (ABM), the simulated agents represent biological entities, such as patients or cells. The rules governing their behaviors in the model are derived from scientific literature and encoded into executable code. Agent-based modeling has been broadly used in biomedical engineering to understand cellular interactions in diseases like lung fibrosis and cancer [6], [7], [8]. It is also commonly used as an *in silico* "test bed" to give high-throughput predictions for therapeutic impacts that are too laborious to test experimentally [9]. Through developing an agent-based model, students will learn more about a disease through researching it, and they will enhance their programming skills through constructing the model code. Students will also learn how to dissect a biological phenomenon into fundamental mechanistic steps that can be encoded in an ABM. The process of learning to build and revise an ABM provides a unique testcase for the use of AI because it is a highly iterative process that requires a baseline understanding of a biological system gained through reading literature and the technical skills for the coding implementation. In this study, we aim to investigate student perceptions of using AI to study and make predictions about complex biomedical systems in the context of learning how to develop ABMs. We also aim to explore how previous AI use and education level (graduate vs. undergraduate) inform AI use and perceptions.

Background

Since the widespread release of AI tools in 2020, their role in educational contexts, particularly in higher education have received increasing attention. AI is evolving rapidly and has surpassed human abilities in many different tasks[10]. This is evidenced by a steady expansion of work being done that centers on AI. Research into the impacts of AI on higher education have become more common, and according to Standford University's 2025 Artificial Intelligence Index Report, the number of publications related to AI has tripled between 2013 and 2023, and the percentage of computer science publications about AI has risen from 21.6% in 2013 to 41.8 in 2023[11]. This emerging body of work includes research on the development of AI-enabled instructional tools, automated assessment tools, and the pedagogical implications of using AI to teach and learn. Given the rapid evolution of contemporary generative AI tools, our review of the literature will focus on studies published after 2020 and work that was conducted in higher education institutions in the United States.

Many prior studies examined the performance of AI tools in the context of college-level coding assignments, engineering design problems, and written assignments[12], [13]. Across different subjects, AI tools were shown to meet or exceed the performance of students who complete the same assignments. In a 2025 study at The University of Illinois Urbana-Champaign, researchers found that ChatGPT earned an 82.24% in an introductory aerospace engineering course, only slightly below the class average, which was an 84.99%[14]. In a 2024 online biomedical and health informatics course at Oregon Health and Sciences University, researchers tested the performance of multiple different AI tools on course exams. The different AI tools performed well on course material, consistently scoring in the 50th percentile and above, with the best AI models exceeding the performance of two-thirds of students. Notably, AI tools provided longer and more complex responses in a shorter amount of time than students[15]. These findings highlight the technical capabilities of AI tools in diverse contexts, but also the heightened concerns about the erosion of academic integrity and the evolving nature of teaching and learning in engineering[3]. However, many of these studies only evaluate AI-generated outputs and do not investigate how students interact with AI throughout the learning process. Authentic student perspectives through their own words, for example in written reflections, are frequently excluded from this literature, leaving a limited understanding about how, when, and why students use AI.

Medicine is one of the fields most rapidly embracing AI technologies[2], [16]. These include language tools for use in the clinic and technologies for medical imaging, analyzing omics data, and clinical trials. Biomedical engineers are at the critical intersection of engineering and medicine, working to improve human health through engineering. Biomedical engineering researchers are essential contributors to the research being done to enable medicine to adopt AI. Since biomedical engineers occupy such a critical space, there is a growing consensus that biomedical engineers must develop technical proficiency with AI tools as part of their professional preparation[17], [18]. Contemporary biomedical research increasingly integrates AI as a supporting analytic tool. AI tools have enabled analysis that was not previously possible in fields like drug discovery or image analysis[18], [19], [20]. However, the emphasis on AI in biomedical engineering research has not been consistently translated to the biomedical engineering classroom. Despite the central role of AI in omics data and system biology, there are minimal studies that examine the use of AI tools in the biomedical engineering classroom, and how it impacts students' understanding.

Our study builds on prior work about AI in the classroom and addresses this gap by examining both the technical utility of AI tools and students' experiences when using AI in biomedical engineering courses. In a combined graduate and undergraduate course, students were tasked with creating an agent-based model of a biological system, and they were then asked to use AI to revise and recreate their model. We investigated student perceptions of AI alongside the effectiveness of AI tools through a concurrent mixed methods approach. Students completed a quantitative survey in the first week of class that asked how helpful students thought AI would be, which was followed by a survey after they completed their computational model that examined how helpful students thought AI was. Additionally, students completed a structured assignment that used AI to revise their computational model. By combining qualitative and quantitative student perspectives alongside a technical examination of the functionality of AI, this study offers insight into how AI can be deployed as a tool in biomedical engineering education and how students experience and evaluate its role in their learning.

Methods

In this study, we employed a concurrent mixed methods approach to investigate how our participants used generative AI to develop an ABM in a biomedical engineering course. Participants' interactions with AI were highly complex and contextual, and these patterns cannot be fully understood through Likert-scale survey questions alone. Quantitative survey responses provided information about trends in student understanding and confidence but risked oversimplifying the data. Therefore, qualitative reflections were collected from participants to give further insight into the emotions, reasoning, and other factors that informed survey responses.

This research was conducted in a combined undergraduate and graduate level biomedical engineering course during the 2025 spring semester at a highly-selective R1 University in the mid-Atlantic region. Students learned different computational modeling approaches for system biology, in a class called Computational Modeling for Biomedical Engineers, a pseudonym. There was no formal policy regarding the use of generative AI tools during the course, allowing for insight into how participants use AI generally in a class setting.

Class Context

In the class, students were placed into groups of 3-5 students. All graduate students were placed into their own two groups of only graduate students to ensure comparable experience levels and knowledge within teams. Each group was tasked with developing an ABM representing a biological system of their choosing over the five week module. Groups chose to model topics such as atherosclerosis progression, granuloma formation in tuberculosis, and the therapeutic effects of combination inhibitor therapy in colorectal cancer. While some students had prior research experience related to their chosen system, no group was constructed with all members being experts in the system they were modeling.

During the first week of class, students independently completed a Likert scale pre-survey assessing prior use of AI and perceived usefulness. The survey had four questions assessing how frequently students had used AI tools to read papers, write code, write papers, and solve general academic problems. Five questions asked for student perceptions about AI tools in general (Supplemental Table 1).

After developing their ABMs using NetLogo, a computational platform commonly used for the creation of ABMs, students independently engaged in a structured interaction and revision process with AI[21]. Students were allowed to choose which AI tool they used because the study team assumed that it would be unlikely that different AI tools would exhibit marked technical differences or differentially impact student understanding. Students uploaded their model rules to ChatGPT (n=27), Microsoft CoPilot (n=2), and Perplexity AI (n=1) and prompted their chosen AI tool to generate NetLogo code from the rules and modify the ruleset to improve the accuracy of the model. Specifically, students copied and pasted the prompt, "Based on the given problem statement, create a set of rules for an agent-based model derived from the literature and provide sources." Separately, students submitted their model's unmodified code to the AI tool and asked the AI tool to revise it. Students copied and pasted the prompt, "Improve on the code and rule set based on our problem definition." Students then attempted to run the modified code on NetLogo.

In the end, students turned in their original code, AI-generated rules, AI-generated code, and the transcript of their AI interactions.

After the completion of their model modifications using AI, participants took a post-survey with 18 Likert-scale questions. These questions assessed the perceived helpfulness and educational value of using AI tools for coding and conceptual understanding (Supplemental Table 2). Students also completed a written reflection about their overall experience using AI for this assignment and their use of AI throughout the ABM module of this course for a completion grade. The reflection questions prompted students to evaluate how AI tools impacted their understanding of their system and to evaluate the functionality of AI tools for writing code. Specifically, students were asked the following questions:

> In approximately one paragraph, explain your experience using generative AI tools to revise and conceptualize your agent-based model.
>
> Consider how these tools influenced
>
> - The development and revisions of your model's rules
> - Your ability to write, debug and refine your model's NetLogo code
> - Your understanding of the biological system you were modeling

Participants were asked to submit written reflections and code separately.

Participants

All students completed both the surveys and the written reflection as part of the course, and data used in this study comes from the subset of consenting participants. Consenting participants included 7 first- and second-year doctoral participants and 23 undergraduate participants. Demographic information was not collected as it was not relevant to the research questions guiding this study. Approval for this study was obtained from the Institutional Review Board and participants provided informed consent for participation.

Analysis

All quantitative data was collected on a five question Likert Scale, with 1 being "strongly disagree" and 5 being "strongly agree." These data were treated as continuous for statistical analysis. Since the data were not normally distributed and there were different numbers of graduate and undergraduate participants, the data did not meet the assumptions for a parametric analysis. As a result, all comparisons between undergraduate and graduate responses were conducted using a two-tailed Mann-Whitney test. Results are reported where n represents the number of students, U is the test statistic. and p is the probability that a value is more extreme than the measured U. All correlation was calculated with a two-tailed Spearman's Rank correlation. In the results, significance was determined at an alpha of 0.05. All statistics were conducted and visualized in GraphPad Prism (Version 10.0).

For qualitative analysis, a list of inductive descriptive codes was generated by the first author based on the observed trends in written reflections (Table 1)[22]. To establish inter rater reliability, the second author coded 18% of responses until they reached 88% agreement with the first author. Discussions of disagreements led to refinement of the code definitions. The final codebook was used by the first author to code all written reflections from consenting students. All collected qualitative data were included in the analysis to avoid selection bias.

Table 1. Qualitative Codes Used by Authors to Code Student Responses

Code	Definition	Student Example
(A) Helpful for writing code	Student describes AI being helpful for writing some component of the code	"ChatGPT also extremely helped with debugging when certain parts of the code weren't working correctly."
(B) Unhelpful for writing code	Student describes AI tools being inadequate/unhelpful for writing code. This is separate from the student describing code implementation problems (see K).	"it was not very successful in creating Netlogo code"
(C) Helpful for model conceptualization	Student describes AI being helpful in initial stages of model development. Describes something about how they created their model in the beginning (scale, translating rules to code, etc.)	"initially, it helped conceptualize rule development by offering structured logic and alternative ways to simulate interactions within the biological system"
(D) Unhelpful for model conceptualization	Student describes challenges using AI to conceptualize their model	"However, not many of its ideas would be easy to directly implement."
(E) Increased understanding	Student describes some form of increased understanding/knowledge of writing code or their biological system by using an AI tool.	"The structured explanation for each improvement followed by the justification improved my overall understanding."
(F) Overall positive experience with AI	Student describes having an overwhelmingly positive impression of AI after the course. This code should only be selected on the large-scale if students describe an overwhelmingly positive experience with AI in writing code and creating the other parts of their model.	"Overall, my understanding of the lung and how tuberculosis interacts with biological components of the lung was increased by using AI."
(G) Overall negative experience with AI	Student describes having a negative impression of AI after the course. This code should only be selected on the large-scale if students describe an overwhelmingly negative experience when using AI to write code and create other parts of their model.	"I find using generative AI to revise and conceptualize my agent-based model extremely frustrating and more time consuming than useful"
(H) AI saves time	Student describes AI expediting some component of the model-building process (code, rules, finding sources, etc.).	"AI was impressively able to quickly synthesize information from the literature to create the ruleset"
(I) AI was helpful for developing model rules	Student explicitly describes AI being helpful for writing model rules. Should include the word, "rule" or some derivative.	"The generative AI tool that I used did a phenomenal job generating a ruleset for me. The rule set was obviously more advanced, sophisticated, and ambitious than what me and my group had come up with"
(J) Disconnect	Student describes a "disconnect" between what AI states it will do and what it did in terms of the stated rules and those rules being implemented in code.	"the AI doesn't really know how to connect the ideas with the process of making an ABM, and it was absolutely hopeless on adding to the code directly."
(K) Code implementation problems	Students state that the code generated by AI did not run. This code also encompasses students saying they have to frequently update/modify the code initially provided by the AI tool.	"ChatGPT had good suggestions for incorporating biological relevance into our model's rules but poor execution of those rules in the code it wrote."
(L) AI provided detailed explanation	Students remark at the detail in explanation from AI.	"The structured explanation for each improvement followed by the justification improved my overall understanding"

(M) AI provided something students had not considered	Students describe AI providing additional insights/information they did not include initially	"It helped me conceive of new ways to construct the model using rules I hadn't considered implementing"

Positionality

Our research team included two of the four faculty instructors for the course, one of whom holds an administrative role in the biomedical engineering department. Other authors include two faculty instructors for an introductory engineering course, an instructor from a different university's biomedical engineering department, and one undergraduate biomedical engineering student who was not enrolled in the course. This combination of authors allowed us to balance perspectives from within and outside of biomedical engineering while also considering student perspectives. The first author is generally familiar with different AI tools but prefers not to use them for school and extracurricular activities, which informed her motivation to engage in this research.

Results & Findings

Overall, participants felt that generative AI tools were helpful in supporting their work in the course. In the post survey, 73.3% (n=22) of participants agreed (n=18) or strongly agreed (n=4) that, "AI tools were helpful in Computational Modeling for Biomedical Engineers" (Table 3). Notably, this was consistent with student's initial perceptions at the beginning of the semester, as in the pre-survey 76.7% (n=23) participants agreed (n=11) or strongly agreed (n=12) that AI tools can be helpful in the course (Table 2). These data suggest that students' prior expectations largely aligned with their experience using AI. However, the number of participants who strongly agreed that AI tools would be helpful decreased by 26.7% (n=8), suggesting that AI may not have been as helpful in practice as participants initially assumed (Table 3). The written reflections provided further evidence of this trend. For example, one undergraduate participant stated, "ultimately, the use of ChatGPT was net positive, but it did produce some code with syntactical errors and logic issues." Another undergraduate student stated that, "Overall, ChatGPT had good suggestions for incorporating biological relevance into our model's rules but poor execution of those rules in the code it wrote." These student responses are emblematic of themes that were conserved across many student reflections. Thus, students may find generative AI tools to benefit them in computational modeling, but it may not be as helpful in practice as they expect. We will explore this trend throughout the results and findings.

Table 2. Student Perceptions of AI in Computational Modeling for Biomedical Engineers

	Strongly Agree		Somewhat Agree		Neither agree nor disagree		Somewhat Disagree		Strongly Disagree	
Survey Questions	n	%	n	%	n	%	n	%	n	%
Pre: AI tools can be helpful in Computational Modeling for Biomedical Engineers	12	40	11	36.6	7	23.3	0	0	0	0
Post: AI tools were helpful in Computational Modeling for Biomedical Engineers	4	13.3	18	60	3	10	4	13.3	0	0

Participants Found Benefits from Using AI

Participants frequently felt that AI tools were most helpful for developing and conceptualizing the foundational framework for their ABMs rather than writing the model code. Participants reported that AI assisted with tasks such as identifying relevant agents and articulating the behavior and relationships of agents within the system. For example, in a written reflection, one undergraduate participant explained that,

> the generative AI tool that I used did a phenomenal job generating a ruleset for me. The rule set was obviously more advanced, sophisticated, and ambitious than what me and my group had come up with, but it is something like what we envisioned for an agent-based model if we had an infinite amount of time to build the model.

This student's statement highlights how efficacious AI tools are for generating biologically relevant and more complex rules than the student could on their own in a fraction of time that it would take the student. Another undergraduate student added that, "the AI-assisted process helped me critically evaluate my model's rules and identify gaps in how interactions were being represented." For this student, AI provided a different perspective that allowed them to see some of the shortcomings in their own understanding of their model. The student also felt that the AI tool connected concepts that the student was unable to without assistance. Providing more specificity, another undergraduate student wrote that,

> Using generative AI helped me to refine the model by providing feedback and code edits that better aligned with the rules and biological problem statement we had established. It helped incorporate elements such as probability of the drugs effectively killing the cancer cells and a better time-based dynamics to represent cancer proliferation and the time it takes the drugs to work.

In agreement with the qualitative findings, survey responses indicate that over half the participants (56.7%, n=17) felt that AI tools helped them translate biological concepts in their ABM rules (Table 3). Additionally, 56.7% (n=17) of participants felt that AI tools increased their understanding of how to create a computational model of a biological system. Thus, students may find AI tools beneficial in developing a framework and translating biological concepts for modeling, and use of these tools might also help students better understand how to create a model.

When creating their ABMs, 63.3% (n=19) reported in the survey that AI tools provided examples or explanations that increased their understanding of agent based modeling (Table 3). This was corroborated by qualitative evidence, as one participant stated in their reflection,

> I did think that my understanding of the biological system I was modeling improved. ChatGPT went piece by piece through the code and explained the rule that went along with it, the logic behind the rule, and how it was biologically relevant to [chronic obstructive pulmonary disease] COPD.

By using AI, this student felt that they gained an understanding of the biological system, but also how they could create an ABM of that system. Together, these results suggest that students still feel like they are learning when they use AI and AI feedback.

Fifty percent (n=15) of participants felt like AI tools reduced the overall time required to develop their model, and most participants (63.3%, n=19) reported that AI-generated instructions and additions to model rules were clear and easy to understand. These results indicate that the use of AI may have helped students build ABMs more efficiently.

Table 3. Student Learning Benefits from Using AI according to Post Survey Answers

Post Survey Questions	Strongly Agree		Somewhat Agree		Neither agree nor disagree		Somewhat Disagree		Strongly Disagree	
	n	%	n	%	n	%	n	%	n	%
AI assistance enhanced my ability to translate biological concepts into a computational model.	5	16.7	12	40	7	23.3	4	13.3	2	6.7
Working with AI tools helped me better understand how to create a computational model of a biological system.	5	16.7	12	40	7	23.3	4	13.3	2	6.7
AI tools reduced the overall time I spent developing my model.	7	23.3	9	30	8	26.7	2	6.7	4	13.3
AI tools provided examples or explanations that deepened my understanding of agent-based modeling.	5	16.7	14	46.7	6	20	5	16.7	0	0
AI suggestions for my model code were clear and easy to understand.	5	16.7	12	40	6	20	5	16.7	2	6.7
I feel confident that I could create another agent-based model by myself (without any generative AI assistance).	13	43%	7	23.3	7	23.3	3	10	0	0
ChatGPT could create an agent-based model without human interference.	0	0%	2	6.7	2	6.7	11	36.7	15	50
AI tools were able to correctly implement rules into code.	1	3.3	8	26.7	7	23.3	8	26.7	6	20

Participants Reported Challenges Using AI

Despite noting an overall benefit to using AI, participants consistently reported challenges when using AI to build and develop an ABM in NetLogo. Several participants expressed frustration with the disconnect between what the AI said it was doing and the code it produced. For example, one participant wrote, “The AI doesn't really know how to connect the ideas with the process of making an ABM, and it was absolutely hopeless on adding to the code directly.” Additionally, another student remarked that, “not many of its [AI] ideas would be easy to directly implement.” These quotes highlight the clear disconnect between the conceptual assistance AI was able to provide and the actual coding implementation. This claim is exemplified by Figure 1, which shows a representative model created by a participant compared to one generated using AI. Overall, participants felt that AI provided overly-ambitious suggestions for their model that could not be implemented by the student or AI tool in their model. These results suggest potential limitations to the usefulness of AI in helping students generate models.

Many participants specified that the AI-generated code contained fundamental structural and syntactical errors that undermined its useability. One participant characterized the experience of, “using generative AI to revise and conceptualize my agent-based model extremely frustrating and more time consuming than useful.” Another participant felt that “the generated code contained fundamental errors, such as duplicate go functions and a missing end command, which made it unusable without manual corrections.” Although the AI tool rapidly produced code, participants frequently felt that substantial effort was required to debug the code, potentially negating the perceived gains in efficiency. Nearly half of participants (46.7%, n=14) disagreed with the statement that AI tools were able to correctly implement model rules into code (Table 3). Commenting on both previous observations, another undergraduate participant stated that,

> When it came to writing and debugging my NetLogo code, ChatGPT’s suggestions often resulted in errors and were difficult to implement correctly. Even after repeatedly asking it to debug the issues (such as the inconsistencies of variable names), the model still was not functioning as expected. While it provided general guidance on the NetLogo syntax and structure, I ultimately had to manually troubleshoot and rewrite parts of the code myself, though I have failed.

This participant describes repeated attempts to debug the AI-generated code, noting persistent issues like inconsistent variable names. Attempting to correct these errors required significant manual effort from the participant, but the participant was ultimately unsuccessful. This experience highlights how turning to AI for NetLogo code generation can lead to the illusion of increased efficiency but may leave students feeling frustrated and using significant effort to correct coding mistakes rather than learning about ABMs.

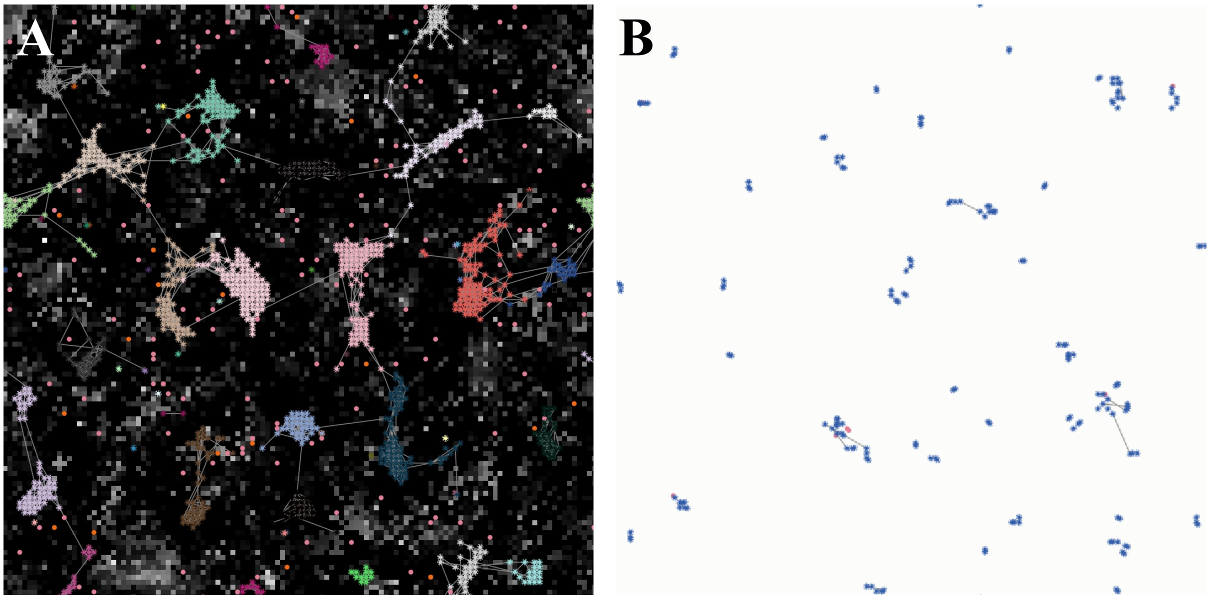

Figure 1. Representative example of ABM produced in Computational Modeling for Biomedical Engineers. This student created a model of how fetal alcohol syndrome affects neurodevelopment. **A)** Student generated model of neural synapse. **B)** Generative AI-created model. There are noticeable qualitative differences in model output complexity evidenced by decreased shapes (representing neurons) and connections between them (grey lines representing synapses).

In the pre-survey, 93.3% (n=28) of respondents thought that AI tools would be helpful for writing code (Table 4). However, only 23.3% (n=7) participants in the post-survey felt that AI tools were helpful for writing code when they were unsure of how to proceed with coding (Table 4). These results suggest that while participants thought that AI tools would be helpful before the course, in practice participants felt they could not rely on AI tools to help them when they did not know what to do next. Furthermore, in the post-survey, 86.7% (n = 26) of participants disagreed that ChatGPT (a generative AI tool) could autonomously create an ABM (Table 4). In the post-survey, 66.7% (n = 20) of participants felt that they could create an ABM without the assistance of generative AI tools (Table 4), suggesting that while participants used AI tools for support, they still feel like they learned the concept of building an ABM. Students' primary challenge to using generative AI to assist in building an ABM may be in the process of writing code.

Table 4. Technical Performance of AI in Coding and Developing an ABM

	Strongly Agree		Somewhat Agree		Neither agree nor disagree		Somewhat Disagree		Strongly Disagree	
Survey Questions	n	%	n	%	n	%	n	%	n	%
Pre: I think generative AI tools will be helpful for writing code.	15	50.0	14	46.7	1	3.3	0	0.0	0	0.0
Post: AI tools were helpful for w riting code when I was uns ure what to do.	7	23.3	16	53.3	4	13.3	2	6.7	1	3.3

Post: ChatGPT could create an a gent-based model without human interference.	0	0.0	2	6.7	2	6.7	11	36.7	15	50.0
Post: I feel confident that I could create another agent-based model by myself (without any generative AI assistance).	13	43.3	7	23.3	7	23.3	3	10.0	0	0.0

Participants Reported Conflicting Experiences with AI

In the written reflections, participants reported conflicting experiences with the use of AI tools. While many participants initially expressed optimism about AI tools supporting the model building process, these expectations were not always realized. One participant described that they were, “slightly optimistic that ChatGPT could provide some useful suggestions and ideas for improving my team’s NetLogo model; however, my optimism rather quickly turned out to be unfounded.” This response highlights how participants felt that AI tools were ultimately less helpful than they had anticipated. The majority of participants found some utility in using AI tools, even if it was limited. This dichotomy highlights the disconnect between how participants perceive the usefulness of AI and how it may be implemented in their class assignments. Additionally, many participants shared conflicting conclusions about the utility of AI within their individual reflection. One participant described how, “using generative AI to revise and conceptualize my agent-based model made it a lot faster to generate code and seemingly made it more efficient” but they also emphasized that, “ensuring that the AI-generated variables were correctly structured within NetLogo wasn’t that easy.” That participant further explained the substantial effort required to debug the erroneous AI-generated code, including repeated iterations with AI and manual debugging. In the end, that same participant ultimately concluded that, “the overall process was more efficient than writing the model from scratch.” Together, these findings suggest that some students approach AI tool use with the strong expectation that AI tools will inherently increase efficiency. For some participants, this perception persisted even when they encountered non-trivial implementation errors. Students’ willingness to invest time and effort into debugging AI-produced errors suggest that AI tools may shift where students use the most cognitive effort. Instead of focusing on the process of building and understanding the model they have created, students may focus more on interpreting and debugging outputs from generative AI.

Graduate and Undergraduate Participants Used AI Differentially

Within the class, undergraduate and graduate participants had different experiences using AI. However, these findings should be cautiously interpreted due to the relatively small number of graduate participants in the study. Overall, the undergraduate participants appeared to find AI tools significantly more helpful (median: 4.0, n=23) than graduate participants (median: 3.0, n=7) in Computational Modeling for Biomedical Engineers (U=30, p=0.004, Figure 2A). Undergraduate participants were also more likely to report that AI tools decreased the time required to develop their models (median: 4.0, n=23) compared to graduate participants (median = 2.0, n=7; U=36.5, p=0.023, Figure 2B). We hypothesize that this difference might be caused by undergraduate students developing greater fluency with AI due to increased exposure and use. However, graduate participants appeared significantly more confident in their belief that they could create another ABM independently (without AI tools; median = 5.0, n=7) than their undergraduate counterparts (median = 4, n=23; U=31, p=0.012, Figure 2C). Many of the graduate participants in this study completed the majority of their undergraduate education prior to the widespread availability of generative AI tools, likely requiring them to develop problem solving strategies without access to AI. As a result, the graduate participants may engage with AI tools differently than their undergraduate counterparts who have experienced the majority of their undergraduate education alongside these AI tools.

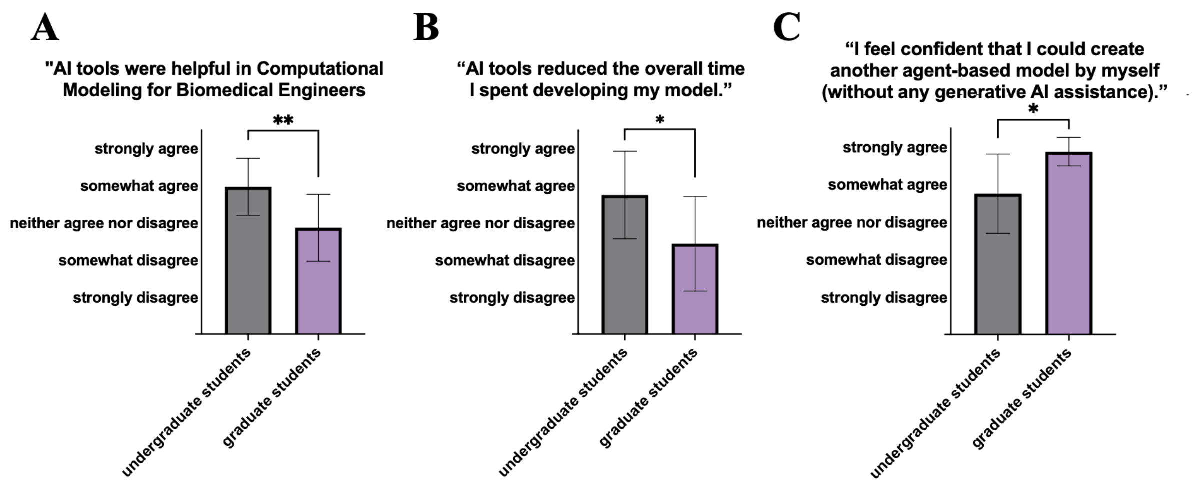

Figure 2. Undergraduate compared graduate experience with AI. Purple bars represent graduate students (n=7), grey represents undergraduate (n=23). All statistics were conducted using a Mann U Whitney test looking for an alpha of 0.05; *=p<0.05, **=p<0.001.

Prior AI Use Correlated with How Participants Interacted with AI

AI use prior to this course was assessed using the pre-survey. Prior to the course, participants reported using AI tools, on average, approximately once every two weeks for assistance completing a coding assignment (Figure 3A). Further, participants reported using AI tools, on average, approximately once every two months to aid in reading academic papers and technical writing (Figure 3B, C). When asked how frequently they used AI to solve general academic problems, the data was bimodal, with participants reporting that they either used AI tools approximately every week or never. Compared to graduate participants, undergraduate participants reported significantly more frequent AI use for solving academic problems (U= 38, P=0.0289, Figure 3D) and to understand academic literature (U=28.5, p=0.0072, Figure 4B).

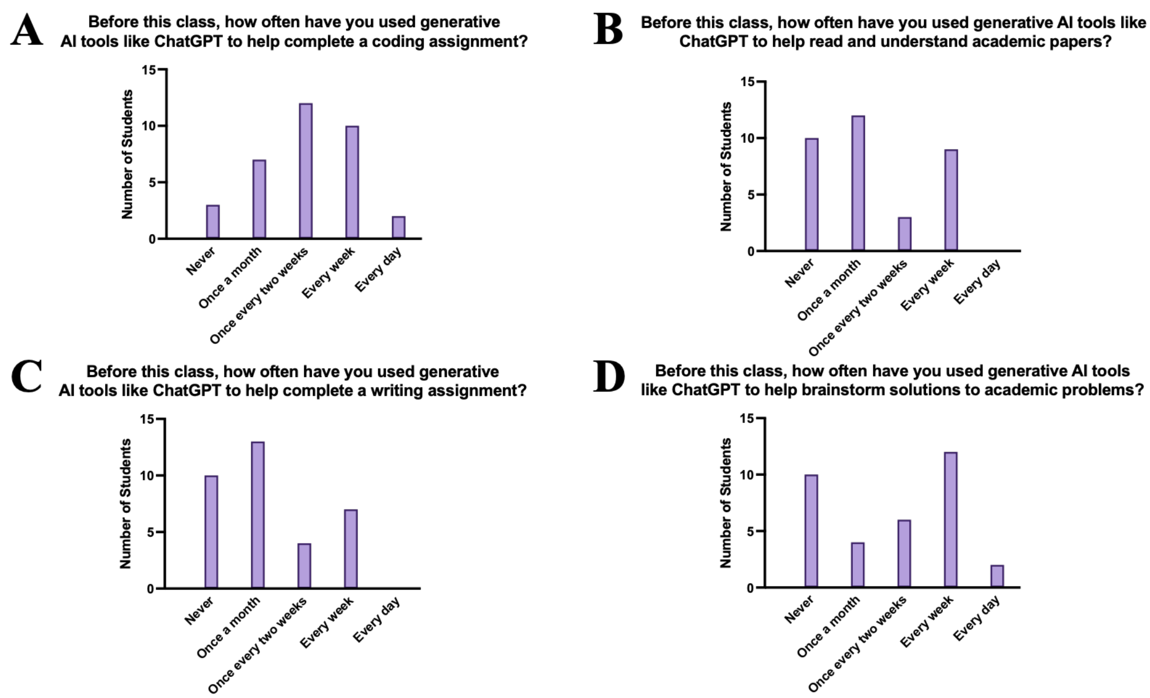

Figure 3. Frequency distributions for previous AI use among students in the class. Each subpanel represents aggregate student responses to each question (n=30).

Prior AI use was positively correlated with perceived helpfulness of the AI tools during the course ($p=0.014$, $R=0.4437$, 95% CI = [0.08830 to 0.6989]). Participants who reported that they used AI tools more frequently to solve academic problems in the pre survey were more likely to report that AI reduced the amount of time they spent creating their ABM in the post survey ($p=0.0103$, $R=0.4612$, 95% CI = [0.1100 to 0.7100]). Additionally, increased reported AI use before the class was correlated with participants reporting that AI tools increased their understanding in the post survey ($p=0.0175$, $R=0.4307$, 95% CI = [0.07228 to 0.6906]). However, increased reported AI use was also negatively correlated with student confidence in creating an ABM independently in the post survey ($p=0.0002$, $R= -0.6323$, 95% CI = [-0.8123 to -0.3425]). These data suggest there is a potential trend where participants who used AI more frequently felt less confident in their abilities to construct a new ABM without it. Together, findings suggests that while frequent AI use may lead to immediate conceptual and efficiency benefits, students may also develop an increased reliance on AI.

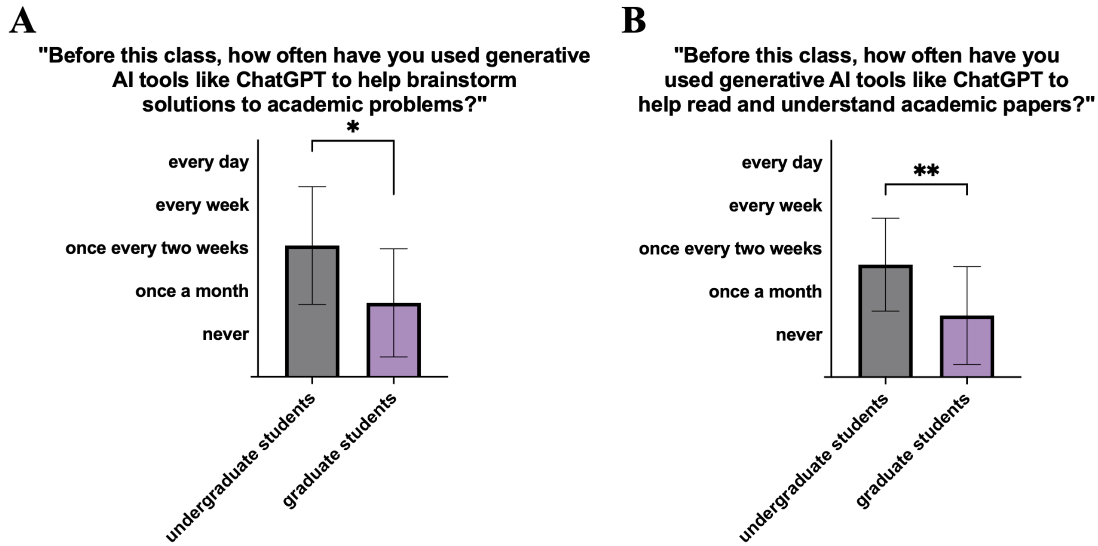

Figure 4. Undergraduate compared to graduate AI use frequency. Purple bars represent graduate students (n=7), grey represents undergraduate (n=23). All statistics were conducted using a Mann U Whitney test looking for an alpha of 0.5; *=p<0.05, **=p<0.001.

Limitations

While this study provides interesting insight into emerging trends in biomedical engineering education, all results should be cautiously interpreted in the context of the study limitations. Firstly, this study has a relatively small sample size comprised of 30 total students with 7 graduate students and 23 undergraduates. Comparisons between the groups may reveal subject specific differences, not broadly representative trends. Additionally, this study was conducted using NetLogo, which represents a major confound. NetLogo is an uncommon coding language, and some of the challenges that students experienced with coding in the NetLogo platform could be attributed to limited AI data coverage. Students may have reported a more positive experience if they used a more common coding language. Additionally, we assumed that each AI tool would produce a similar result. However, since each AI tool has a slightly different architecture, students likely had differential experiences depending on what AI tool they used. These tool-specific differences were not investigated in the present study.

Discussion

Participants reported that AI tools provided more complexity and biological relevance to their ABMs. AI tools were reported to supplement participants' understanding of the system they were modeling, and the fundamental principles of constructing an ABM. Participants who frequently used AI for other classes and assignments reported a greater proficiency with AI tools, but this was also correlated with lower confidence in their abilities to construct a new ABM without using AI, potentially pointing to feelings of dependence on AI that need to be investigated in future research. This observation is consistent with emerging trends across higher education [23], [24]. Many participants also noted a clear disconnect between the model AI said it had encoded, and the actual code. The code produced by AI was erroneous, and participants frequently described having to correct syntax and debug errors. AI tools were helpful for showing participants how to create an ABM, but they were unhelpful with the practical process of creating the ABM, specifically the translation between putting model rules into code[25]. This could likely be due to the fact that NetLogo is not a common coding language and AI tools were not trained using NetLogo, as it is a relatively niche programming language. Additionally, each student engages with AI differentially for both the class and outside of the class, which could have informed their responses. Participants who use AI more in other classes or other activities could have leveraged AI in a way that participants who did not use AI could not [26], [27]. These data also suggest that AI use could increase AI proficiency, so there may be value in teaching targeted AI use that allows participants can leverage AI for understanding, not to undermine learning.

Conclusions

Overall, these data suggest that while AI can support participants in learning and building computational models of biological systems, there are some potential drawbacks. AI tools can provide clear and concise explanations that can provide personalized feedback on their model and the model building process. However, many students also report that AI was not as helpful as anticipated for writing code in NetLogo or translating model rules into code. Additionally, many students noted that the AI tool would propose something far more complex than what it would encode, creating confusion. Within the class, the graduate students used AI less frequently than their undergraduate peers and felt more confident in their abilities without AI, suggesting that consistent AI use can cause students to become dependent on AI. Together, these results suggest that there could be an advantage to teaching targeted use of AI to biomedical engineers, especially given the field's proximity to healthcare. Future work will examine the use of AI in other types of computational modeling using different programming languages (Python, MATLAB, R) and will include faculty, graduate, and undergraduate perceptions of AI use in the classroom.

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Supplemental Tables

Supplemental Table 1. Pre-Survey Questions

Question 1	Before this class, how often have you used generative AI tools like ChatGPT to help complete a coding assignment?
Question 2	Before this class, how often have you used generative AI tools like ChatGPT to help complete a writing assignment?
Question 3	Before this class, how often have you used generative AI tools like ChatGPT to help brainstorm solutions to academic problems?
Question 4	Before this class, how often have you used generative AI tools like ChatGPT to help read and understand academic papers?
Question 5	I am familiar with the limitations and potential biases of generative AI tools.
Question 6	I trust responses from generative AI tools.
Question 7	I think generative AI tools will be helpful for writing code.
Question 8	I think AI tools will be helpful for reading papers.
Question 9	I think AI tools can be helpful in Computational Modeling for Biomedical Engineers.

Supplemental Table 2. Post-Survey Questions

Question 1	AI tools were helpful for writing code when I was unsure what to do.
Question 2	AI tools were helpful for reading papers.
Question 3	AI tools were helpful in Computational Modeling for Biomedical Engineers.
Question 4	AI tools were helpful at identifying a ruleset for my model.
Question 5	AI tools were able to correctly implement rules into code.
Question 6	AI assistance enhanced my ability to translate biological concepts into a computational model.
Question 7	Generative AI gave helpful feedback on my model.

Question 8	I am confident that the additions from generative AI are accurate and will improve my model.
Question 9	Working with AI tools helped me better understand how to create a computational model of a biological system.
Question 10	AI tools made it easier to debug or troubleshoot coding issues in NetLogo.
Question 11	AI suggestions for my model code were clear and easy to understand.
Question 12	AI suggestions for my model rules were clear and easy to understand.
Question 13	Using AI tools helped me evaluate the quality of rules in my model.
Question 14	Using AI tools helped me evaluate the quantity of rules in my model.
Question 15	AI tools reduced the overall time I spent developing my model.
Question 16	AI tools provided examples or explanations that deepened my understanding of agent-based modeling.
Question 17	ChatGPT could create an agent-based model without human interference.
Question 18	I feel confident that I could create another agent-based model by myself (without any generative AI assistance).