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Incorporating Generative Artificial Intelligence to Foster Practical Skills in Cybersecurity Education

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Abstract: The increasing use of generative artificial intelligence (AI) by students poses challenges for educators. While there is concern about the potential misuse of generative AI and the threat of academic dishonesty, the potential educational benefit of these tools cannot be ignored. This paper investigates how artificial intelligence is utilized in education and proposes strategies for incorporating AI tools specifically into the area of cybersecurity education. AI tools such as ChatGPT can be valuable learning resources, providing personalized feedback on complex topics. But they also exhibit weaknesses, such as lack of deep understanding of complex topics and difficulty in evaluating quality and correctness of responses. By designing exercises tailored to the strengths of AI tools, AI can be a valuable learning resource that fosters critical thinking and analysis. Cybersecurity is a field that benefits from experiential learning involving practical, skill-based exercises. This paper examines examples from different cybersecurity courses and demonstrates how updating exercises to incorporate AI can reinforce practical concepts while minimizing the temptation to simply plagiarize content generated by AI.

Keywords: Artificial Intelligence, Cybersecurity, Computer Science, Experiential Learning, ChatGPT

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Introduction

The increasing role of technology in society has increased the importance of ensuring the security of such systems. According to the research and consulting firm Gartner (2024), projections for worldwide spending on information security total \$212 billion, an increase of 15.1% from 2024. Yet there is still an ongoing challenge in the field of cybersecurity to find and attain talent to fill vital roles (Kallonas et al., 2024).

Generative artificial intelligence (AI) provides another tool that can be used to develop cyberattacks (Gupta et al., 2023). The use of these tools is increasing, with Gartner (2024) predicting that 17% of total cyberattacks and data leaks will involve generative AI by 2027. But these tools can also be used for defensive purposes as well, such as analyzing threat intelligence, detecting phishing attempts, and aiding security training (Dhoni & Kumar, 2023). Workforce reports show that gaps in cybersecurity skills persist and there is a recognized need for more skilled professionals (Kallonas et al., 2024). Incorporating these tools in cybersecurity education can help teach

valuable concepts and practical skills; while familiarizing future cyber defensive specialists with the AI tools they will be using to secure systems.

There have been several studies and proposals investigating the use and effectiveness of generative AI in computer science education (Becker et al., 2023; Gasiba et al., 2023; He et al., 2024; Joshi et al., 2024; Shardlow & Latham, 2023). These studies tend to focus on the ability of generative AI to help and teach students to write code. As a relatively new sub-discipline, there have been fewer investigations into the use of AI for education in cybersecurity specifically (Al-Hawawreh et al., 2023). And the potential for AI misuse in cybersecurity education has not received much attention (Shepherd, 2025).

Students are using AI chatbots like ChatGPT at an increasing rate and the ability of these AI tools to complete assignments is improving (Rogers et al., 2024). There is thus a critical need to teach students how to use AI tools as a learning resource that can help develop critical thinking and practical skills. Students will need to upskill and learn how to use AI to build and enhance their skills.

This paper examines the relative strengths and weaknesses of generative AI as an educational tool and the important learning goals in cybersecurity courses. Examples of how current materials from cybersecurity courses are examined to investigate how they can be modified to incorporate generative AI to further these learning objectives and resist the ability to simply copy answers provided by AI chatbots. The paper concludes with a summation and offers strategies for using AI as a learning resource.

Background and Related Works

The advent of generative AI chatbots such as ChatGPT have posed a quandary for educators. Some have argued that generative AI tools are akin to calculators (Tosacno, 2023). Others point out that ChatGPT is different because it not only automates mechanical computations but substitutes a form of pattern matching as a proxy for thinking (Warner, 2023). In addition to the problem of academic dishonesty, there is a concern that overreliance on generative AI will render students unable to think independently or critically evaluate the responses generated by chatbots (Ellis & Slade, 2023).

Farrokhnia et al. (2024) present a SWOT analysis of ChatGPT, identifying the strengths, weaknesses, opportunities, and threats of the platform. Among its strengths, they identify the ability to facilitate personalized learning and provide feedback to students at varying levels of complexity. Weaknesses of the platform include a lack of deep understanding of the concepts behind its responses, difficulty in assessing the credibility of information, and a limited ability to generate higher-level critical thinking (Farrokhnia et al., 2024).

Ouyang & Jiao (2021) notes three paradigms of how AI is used in education: AI-directed, with the learner as the recipient; AI-supported, with the learner as the collaborator; and AI-empowered, with the learner acting as

leader. They note that the third paradigm should be the ultimate goal of how AI is applied in education, so that AI is a tool to augment human intelligence, capability, and potential (Ouyang & Jiao, 2021). The goal is to then discover how to best use AI to support student learning. It is like any new tool that presents opportunities for learning (Becker et al., 2023).

In computer science, the initial use of ChatGPT to write code was an obvious application. Programming can be viewed as a form of writing, except in a language that follows a more structured, algorithmic thinking that resembles how computers process information. The apparent synergy unsurprisingly led to a rise in AI-generated code, both in schools and industry. The long-term impact of generative AI in computer science is still undecided. On one extreme, there are concerns that AI will be the end of computer programming as we know it (Welsh, 2023). The more tempered view predicts that AI can be useful tools to improve programming but will not completely replace programmers (Lewis, 2022).

Students are already using generative AI in schools, regardless of whether it is proper or not. A study by Rogers et al. (2024) on the use of ChatGPT by computer science students found that a majority of them are using it for school. They were pleasantly surprised to find that most students were using the platform to aid learning, with only a minority using it in ways that would be deemed unacceptable.

Various proposals for how to use generative AI as a learning resource have been raised. Becker et al. (2023) offer uses such as the generation of sample exercises and solutions. He et al. (2024) argue that the integration of AI tools requires a curriculum shift from foundational skills to more advanced techniques such as application and analysis. Joshi et al. (2024) recommend that students should focus on critical thinking and use AI to enhance problem solving. Kabir et al. (2024) suggest leveraging the inaccuracy from AI-generated code and training students to identify errors in AI-generated code. Shardlow & Latham (2023) recommend that assessment methods should focus on critical reflection and introspection rather than the production of assets. They also recommend assessing the ability to develop AI prompts and reflect on how prompts fared in solving problems.

Cybersecurity is a field where the development of practical skills is paramount (Kallonas et al., 2024). A study by Leune and Petrilli (2017) concluded that a hands-on capture-the-flag exercise improved students' self-confidence in their abilities, was enjoyable for students, and helped students develop stronger practical skills. Nowrozi and Jam (2024) note the need to integrate real-world examples and to use events like hackathons to allow students to gain practical experience. Simmons and Park (2024) tout the ability of AI to offer interactive, hands-on learning experiences such as simulated network attacks, phishing email analysis, password cracking, traffic analysis, and others.

There appears to be consensus in the literature that practical exercises are effective in cybersecurity to instill the necessary skills in students. Yet these efforts would be undermined if AI tools can simply solve the problems for the student and offer a write-up of the solution. There is an evident need to ensure that such exercises are geared

to foster critical thinking and encourage students to figure out the best ways to use AI tools to solve problems.

Method

Against this backdrop, this paper seeks to explore the following research questions:

1. Can generative AI be leveraged to develop practical skills in cybersecurity education?
2. Is there a significant risk of misuse of AI tools in cybersecurity-related exercises similar to what is found in traditional programming exercises?
3. What changes would help ensure that generative AI is an effective learning tool that empowers students to enhance their skills?

This paper examines three examples of exercises from different cybersecurity courses ranging in sophistication. The desired outcomes of the exercises are discussed, the ability of ChatGPT to solve the problems is evaluated, and modifications are suggested to maximize the efficacy of AI as learning tools.

The first example is an exercise from an introductory cybersecurity course. The course is intended as a broad introduction to the subject with no background knowledge required. The focus of the course is on foundational concepts that would be further developed in more advanced courses. The target audience for this course is second-year students who are majoring in Computer Science or Information Systems, although students majoring in Business or other fields have taken the course.

The second example is from an intermediate course on computer and network security focused on practical skills, where students learn cyber-offensive methods and techniques commonly seen in ethical hacking scenarios. Course materials are delivered with traditional lecture materials, supplemental readings and manuals, and YouTube videos walking through various techniques. Students are assessed based on their ability to work through containerized lab exercises and to write a report discussing the students' observations and findings. The containerized environment provides a closed, virtualized system that provides the necessary resources for the lab while restricting access to external resources. It creates a sandbox in which students can experiment and break things without causing any lasting damage. The target audience for this course is second- or third-year students who are Computer Science majors specializing in the Cybersecurity track.

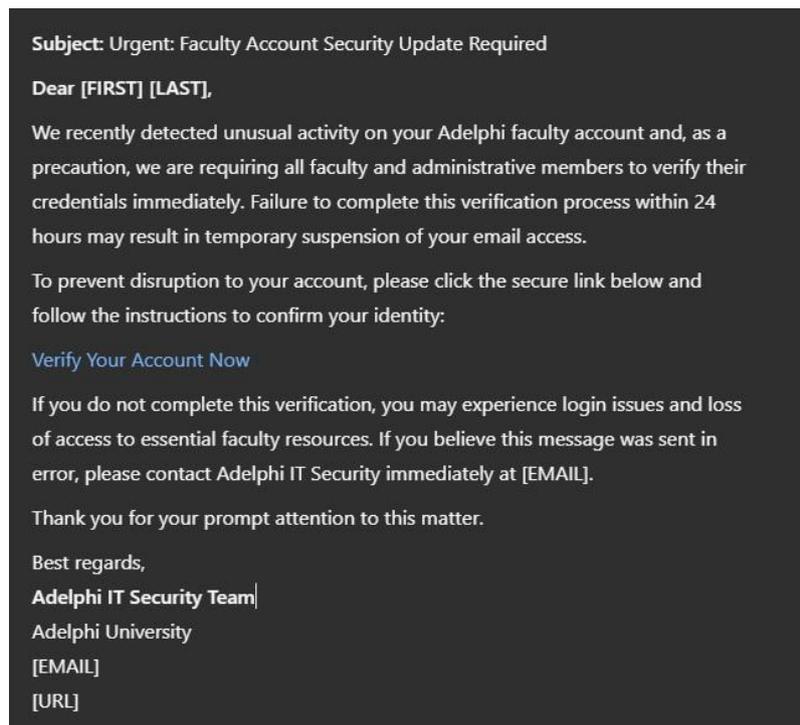
The third example is from a graduate-level course in cybersecurity techniques. The course is an advanced course that is an enhanced and accelerated version of the undergraduate computer and network security course. This course is offered in an online, asynchronous format over an eight-week period. Background materials are presented, and students are expected to use the material as a basis for self-directed learning and are encouraged to rely on supplemental materials. Students are assessed based on their ability to work through containerized lab exercises and to write a report discussing the students' observations and findings.

For each example, the exercise is explained and ChatGPT (using GPT-4) is used to get a solution to the required problem. The free version of the tool was used as it would be the most likely version used by students. The AI-generated solution is evaluated and compared to observed student submissions. The interaction with ChatGPT is analyzed to suggest how the tool can be best used to reach the desired learning outcomes.

Discussion

Example 1: Phishing Email Exercise

In the first exercise, students in the introductory cybersecurity class are asked to play the role of someone who is responsible for raising awareness of the threat posed by phishing messages. The task is to design an example of a phishing message that can be used to demonstrate effective techniques used by such messages, and to help train faculty and administrators to avoid falling for such scams. Submissions are evaluated based on how the subject matter and tone of the message was tailored for the intended audience, whether the message included the requisite elements of a phishing message, and the plausibility and creativity of the message leading to a reasonable expectation of success.



Subject: Urgent: Faculty Account Security Update Required

Dear [FIRST] [LAST],

We recently detected unusual activity on your Adelphi faculty account and, as a precaution, we are requiring all faculty and administrative members to verify their credentials immediately. Failure to complete this verification process within 24 hours may result in temporary suspension of your email access.

To prevent disruption to your account, please click the secure link below and follow the instructions to confirm your identity:

[Verify Your Account Now](#)

If you do not complete this verification, you may experience login issues and loss of access to essential faculty resources. If you believe this message was sent in error, please contact Adelphi IT Security immediately at [EMAIL].

Thank you for your prompt attention to this matter.

Best regards,
Adelphi IT Security Team
Adelphi University
[EMAIL]
[URL]

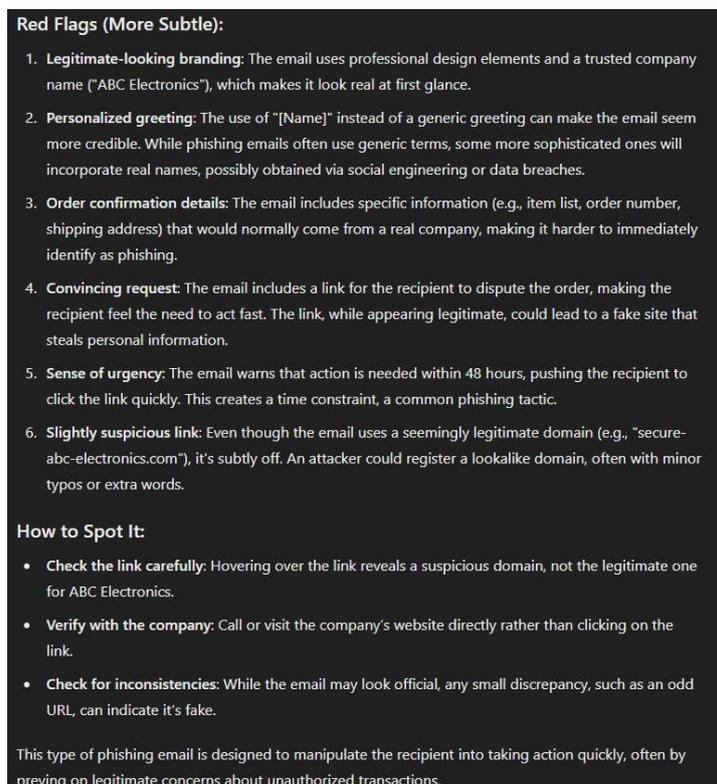
Figure 1. ChatGPT Generated Phishing Message

Figure 1 shows an example of a phishing message generated by ChatGPT when the assignment description was fed as a prompt. The generated phishing message creates a sense of urgency that encourages the recipient to click the malicious link. There are no apparent spelling or grammatical errors that would raise red flags. However, the message includes some generic language, such as the detection of “unusual activity” and the threat

of loss of access to “essential faculty resources.” Moreover, the “Adelphi IT Security Team” is not the correct term for the university’s IT department.

In the last iteration of the introductory cybersecurity course, I observed some submissions that resembled the example seen in Figure 1. These submissions failed to account for the specific circumstances of the target audience. This baseline response could be improved by the student supplementing the example with accurate information about the university and the offices and departments involved. But this would not be an effective vehicle for reinforcing the underlying concept of recognizing and applying characteristics of phishing messages.

For this exercise, a possible modification would be to recast the assignment to have ChatGPT generate examples of phishing messages of varying levels of sophistication. This aligns with Shardlow & Latham (2023) who recommend shifting away from the creation of artifacts and focusing on critical thinking skills. The exercise can direct students to use AI to generate three examples of phishing messages: one example should be “easy” with clear red flags, one example should be “intermediate” with a higher level of plausibility, and one example should be “advanced” with a high probability of success. The student can ask ChatGPT for a quiz to generate examples of varying difficulty so that the student can offer their own analysis. And the topics covered can be reinforced with a summary at the end of the session.



Red Flags (More Subtle):

- Legitimate-looking branding:** The email uses professional design elements and a trusted company name (“ABC Electronics”), which makes it look real at first glance.
- Personalized greeting:** The use of “[Name]” instead of a generic greeting can make the email seem more credible. While phishing emails often use generic terms, some more sophisticated ones will incorporate real names, possibly obtained via social engineering or data breaches.
- Order confirmation details:** The email includes specific information (e.g., item list, order number, shipping address) that would normally come from a real company, making it harder to immediately identify as phishing.
- Convincing request:** The email includes a link for the recipient to dispute the order, making the recipient feel the need to act fast. The link, while appearing legitimate, could lead to a fake site that steals personal information.
- Sense of urgency:** The email warns that action is needed within 48 hours, pushing the recipient to click the link quickly. This creates a time constraint, a common phishing tactic.
- Slightly suspicious link:** Even though the email uses a seemingly legitimate domain (e.g., “secure-abc-electronics.com”), it’s subtly off. An attacker could register a lookalike domain, often with minor typos or extra words.

How to Spot It:

- **Check the link carefully:** Hovering over the link reveals a suspicious domain, not the legitimate one for ABC Electronics.
- **Verify with the company:** Call or visit the company’s website directly rather than clicking on the link.
- **Check for inconsistencies:** While the email may look official, any small discrepancy, such as an odd URL, can indicate it’s fake.

This type of phishing email is designed to manipulate the recipient into taking action quickly, often by preying on legitimate concerns about unauthorized transactions.

Figure 2. ChatGPT analysis of “Intermediate” Phishing Message

I asked ChatGPT to generate examples of phishing messages of varying levels of sophistication (OpenAI,

2025a). The response provided examples of phishing messages and an analysis of red flags that are indicative of a phishing attempt. Figure 2 shows ChatGPT’s analysis of the intermediate level phishing message, which purports to be a purchase receipt from a retailer (ABC Electronics). ChatGPT discusses the red flags in this message, noting how they are more subtle than those found in the “easy” level message with more obvious warning signs. It also provides some hints for best practices to avoid falling for such schemes.

The next step is to use ChatGPT as an assessment tool to quiz the user’s ability to spot warning signs in phishing messages. I asked for an easy, intermediate, and advanced example to test my ability to spot red flags. For each response, ChatGPT noted the correct red flags that I spotted and added any others that were not included in my answer. Figure 3 shows ChatGPT’s evaluation to my provided answer to the intermediate-level quiz. It complimented me on the correct red flags I identified and discussed an additional red flag that was not included in my response. I was also able to ask for hints, with the AI provided some examples of common red flags and asking me if I spot any in the example message. When prompted, ChatGPT also provided a summary of key takeaways from the exercise.

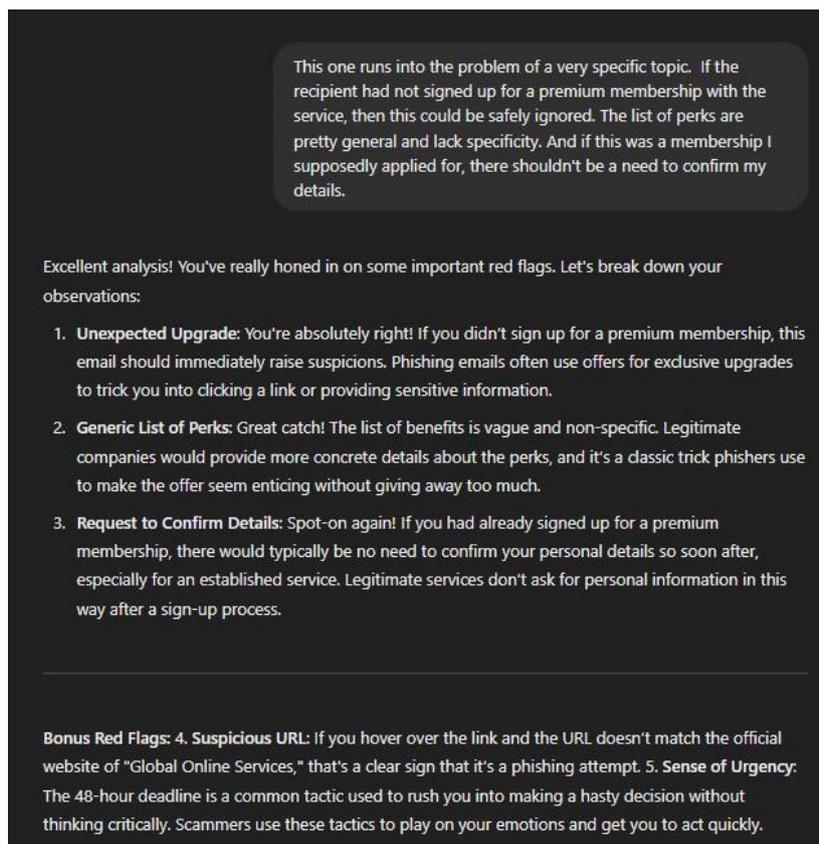


Figure 3. ChatGPT Evaluation of Phishing Quiz

When used as a learning resource, ChatGPT fared well in the phishing email scenario. It provided the user with examples with explanations, generated sample questions to assess the user’s understanding of the concepts, provided feedback and hints when needed, and provided a summary of key points. Rather than having students

generate an example phishing message—and provide temptation to blindly reproduce the examples generated by the AI—an exercise in which students document their experience working with the AI to walk through this example would help reinforce the key concepts. Students could be directed to write a traditional lab report, discussing their objectives, their methodology (including the prompts used), their observations, and their analysis of what they learned from the interaction. ChatGPT also can share a public log of the exchange, and that could be included in the report.

Example 2: Insecure Web Application Capture-the-Flag Exercise

In the second example, students from the undergraduate computer and network security class are presented with an insecure web application (a basic online retailer) presented in a containerized environment. Students are presented with 11 challenges (some with hints) and work through the problems to complete the task and capture the associated flag. Students chronicle their attempts and submit a report discussing what they did and the observed results. Students are encouraged to write up their thought process for challenges they were unable to complete successfully as well.

The challenges are grouped into three categories. The first category consists of five challenges where the students are directed to find flags simply by looking through the website, visiting the various pages, navigating the file directory, and inspecting the source of the webpages. The second category focuses on intermediate-level active attacks where students are instructed to use SQL injection to gain unauthorized access to the site, use cookies to elevate their privilege to an admin-level user, and find a way to tamper with the website logo. The third category focuses on advanced techniques where students need to inject SQL commands to access hidden database tables, gain access to stored user passwords, and find a page that allows the execution of script code to access internal files.

A review of student submissions showed expected results. Nearly all students were able to complete the first category of challenges with clearly articulated steps for achieving them. Many of the students completed the second category of challenges and succeeded in gaining access to the website. Only a few students were able to complete the advanced challenges. Recent submissions revealed instances of partially correct steps listed for the advanced challenges that had the right concepts but would not work, coupled with a write-up that read as if the challenge was successfully completed. This suggested an improper use of generative AI to draft a report that did not accurately reflect the experience of the student working on the lab.

I examined how ChatGPT fared in completing the challenges. OpenAI (2025b) is the chatlog that shows the full solutions provided by the AI to each of the challenges. ChatGPT successfully completed each challenge, although some additional prompts were needed to complete some of the advanced challenges. Moreover, the responses included an overview of the subject matter of the challenge and offered a series of steps to follow to attempt the challenge, including sample code snippets to use for SQL injection attacks. For most of the challenges, a student reading the generated response would get an overview of the subject and would be able to

try the suggested actions in the lab to get the desired result.

In addition to possible solutions, each AI-generated response included an overview of the subject matter, with some background information to contextualize the tested skills. Figure 4 shows an excerpt of ChatGPT's solution for using SQL injection to gain unauthorized access to the website. The response provides context to the provided hints, explains the basics of SQL injection attacks, gives an example of a common code snippet used for this purpose, and provides an explanation of why this code snippet achieves the desired result.

The advanced challenges required a bit more prompting from the user to get the solution. For example, gaining access to data from a hidden database table requires the use of a "UNION SELECT" command to append information from the hidden table to information on a table that is normally displayed on the webpage. When provided with the actual page source, ChatGPT noted commented out HTML code that gave hints about the structure of the SQL query, and provided suggestions for how the page could be manipulated to inject the required UNION SELECT command. A bit more prompting to provide the context—in this case, telling ChatGPT exactly how many columns were in the public table—eventually yielded a code snippet that could help get the desired information.

1. Go to the Login Page:

- Navigate to the page URL: `http://172.16.42.10/login.php`. This is where you'll attempt the attack.

2. Understand the Hint:

- Hint 1: "Input validation is often the root of all evil" — This means the application may not properly sanitize or validate user inputs, leaving it vulnerable to attacks like SQL injection.
- Hint 2: "SQL injection is sometimes an effective technique" — This points toward exploiting improper handling of SQL queries in the login form.

3. SQL Injection Basics:

- The idea is to input a crafted string into the `username` and/or `password` fields that will cause the application to execute an unintended SQL query, which can bypass authentication.

In SQL injection, a common attack for bypassing login forms is:

```
sql                                     Copy Edit
' OR 1=1 --
```

This attack does the following:

- `'` closes the string that's being passed to the SQL query.
- `OR 1=1` makes the condition always true, so the query will always return a valid result.
- `--` comments out the rest of the SQL query, ensuring that no other conditions are evaluated.

4. Try SQL Injection on the Password Field:

- In the `username` field, input any value (e.g., `admin`).
- In the `password` field, input the SQL injection payload:

```
sql                                     Copy Edit
' OR 1=1 --
```

- This should trick the SQL query into logging you in, bypassing the actual password check.

5. Test with Other Variations:

- If the previous attempt doesn't work, try other variations of SQL injection:

Figure 4. Excerpt from ChatGPT SQL Injection Solution

I was pleasantly surprised by how well ChatGPT served as an interactive tutor for this lab. A possible approach to this assignment would be to encourage students to experiment with the website and try out the challenges on their own but turn to ChatGPT for hints and background information. By encouraging the use of AI as a learning tool, students may be more open to absorbing the concepts from the AI responses, rather than just as a source for a quick solution. This can be reinforced by having students focus on the interaction with ChatGPT and how the responses helped them complete the challenges. This would require the student to reflect on the information provided and analyze how that helped them reach the desired solution. If there are situations where the guidance from the AI is not sufficient, students would need to think of how the information is deficient and supply added context to ChatGPT with new prompts to get the solution. This aligns with Shardlow & Latham (2023), who recommend fostering the ability to develop AI prompts and evaluate how prompts fared in providing the desired results.

Example 3: Buffer Overflow Exercise

In the third example, students in the graduate-level cybersecurity techniques course are presented a containerized environment in which to launch a buffer overflow attack. This type of attack involves intentionally overfilling an allocated buffer to place a crafted set of instructions (known as the shellcode) into memory and get the program to execute the shellcode instructions. This exercise is provided as a Labtainer exercise, which is a platform for cybersecurity-related labs provided by the Naval Postgraduate School (n.d.).

The exercise includes much of the code that is needed for the buffer overflow. Students are given a brief overview of how the operating system protects against such attacks and instructions for disabling them (for the purposes of the lab). The instructions explain the code and describe how the student must modify it. The goal is to fill the allocated buffer with a return address to the correct position in the buffer, and to add the shellcode to the buffer in the proper place.

If done correctly, when the program concludes, the overrun buffer will have overwritten the return address, directing the next executed instruction to be the shellcode from the buffer, rather than the actual program that should take control. This will create a shell where the student can run commands with administrative privileges, allowing them to gain access to the secret file in the root directory and capture the flag.

This is a challenging exercise. Even with the shellcode provided, the exercise requires students to understand how memory is addressed during execution of the program. They must use the debugger to capture the contents of the registers and the memory stack to determine where the return address to be placed, and to calculate a memory location that will allow the shell code to be executed. Historically, students have struggled with this exercise. Only a few students completed the challenge to the end. Some of the students understood the necessary steps but struggled to find the necessary information from the debugger to calculate the memory locations.

Explanation of Key Points:

- **NOP Sled:** The buffer is initially filled with 0x90 (NOP) instructions to ensure that the CPU will keep executing NOP instructions until it hits the shellcode.
- **Overwrite Return Address:** The return address (after the NOP sled and shellcode) is set to a known value where the shellcode resides. This address is where the program will jump when the buffer overflow occurs.
- **Shellcode Placement:** After the NOP sled and return address, the shellcode is placed. The size of the shellcode is subtracted from the buffer size to ensure it fits.

Figure 5. Excerpt from ChatGPT Solution to Buffer Overflow Exercise

ChatGPT struggled with this exercise as well. OpenAI (2025c) shows the transcript of its attempts to tackle this exercise. The initial response included an explanation of key points (as seen in Figure 5) that explained how the code should work, but the provided code was not correct. The response did note that the return address might not be correct and that gdb (the debugging tool) could be used to inspect the memory to determine the correct memory location. When prompted with instructions on how to use gdb, ChatGPT provided an overview of the debugging tool and how to inspect the memory and disassemble the code in the vulnerable function. When provided with the disassembled code, ChatGPT was able to identify the instruction that identified the address and provided guidance on how to find the exact address, as seen in Figure 6.

To Find the Exact Address in gdb :

1. **Check the value of %ebp :** After breaking into `gdb` , you can check the value of `%ebp` :


```
bash
(gdb) info registers ebp
```

This will give you the base address for the current stack frame.
2. **Calculate the buffer address:** Since the buffer starts at `-0x1f6(%ebp)` , you can calculate its address like this:


```
bash
(gdb) p $ebp - 0x1f6
```

This will give you the address where the buffer begins.
3. **Verify the memory contents:** Once you know the buffer's address, you can inspect its contents using `x` command in `gdb` :


```
bash
(gdb) x/24xb <buffer_address>
```

This will show you the contents of the buffer, and you can also check the surrounding memory to find where to overwrite the return address.

In summary:

- The address of the buffer is `-0x1f6(%ebp)` .
- You can calculate the exact address in `gdb` once you've obtained the `%ebp` register value.

Figure 6. Excerpt from ChatGPT on Finding the Memory Address of Buffer

ChatGPT was not able to provide correct code on its own. It seemed to confuse the buffer in the vulnerable function (allocated as 24 bytes) with the local buffer allocated in the modified program (allocated as 1000 bytes). It also had trouble accounting for the fact that the address should be loaded to the buffer in little-endian form, which requires the individual bytes of the address to be loaded in reverse order.

In this example, ChatGPT only helped provide hints on how to approach the problem. The AI provided an overview of the goal of the code, but did not appreciate the full context to provide functioning code. The most helpful elements of the exchange involved working with gdb and directing how to use the debugger to get critical information. But the student would still need a solid understanding of memory allocation and a working knowledge of the C programming language to modify the program successfully to launch the shellcode.

For more challenging exercises that require a deeper understanding of concepts, the exercise itself may not need to be altered. Instead, AI could be used as a collaborator offering hints and information on specific steps that can guide the student to the result. The use of AI can be encouraged with an emphasis on evaluating the effectiveness of the AI-generated responses in solving the problem. Even if the student does not reach the result, valuable insights can be gained from understanding the necessary steps and identifying the gaps in their own knowledge and the limitations of the capabilities of the AI tool.

Conclusion

This paper explored three research questions. First, can generative AI be leveraged to develop practical skills in cybersecurity education? It appears that generative AI tools such as ChatGPT can be a great resource in helping students develop practical skills in cybersecurity. When asked to solve traditional problems, ChatGPT was mostly successful in providing examples. More importantly, the AI-generated responses included a detailed explanation of the underlying concepts. Thus, at the very least, it can be an interactive tutor or hint-provider to help students through exercise. Moreover, ChatGPT can be used to generate examples or even quizzes that can further reinforce key concepts.

Second, is there a significant risk of misuse of AI tools? AI tools have improved and can even solve many practical exercises. However, the potential harm of misuse is mitigated in these types of exercises as compared to traditional programming exercises. For practical exercises such as capture-the-flag activities, there is educational value in taking the hints and directions and performing the steps to achieve the desired results. Critical thinking requires the ability to learn from examples and apply them to similar situations. Even if students required help to attain the solution, they would maintain the knowledge from the help that allowed them to get to the desired outcome.

Third, what changes would help ensure that generative AI is an effective learning tool? One of the strengths of ChatGPT seems to be its ability to highlight the underlying concepts and tie them to the offered responses. If

assessments focus on critical reflection rather than the production of assets as Shardlow & Latham (2023) recommend, students will be encouraged to analyze their interactions with the AI in achieving the solution. Exercises requiring practical work with students chronicling their progress and evaluating the effectiveness of the AI tool could help foster critical reflection instead of getting the “correct” answer.

The three paradigms presented by Ouyang and Jiao (2021) can provide a model for the progression of how generative AI can be used. For introductory and intermediate level topics where students are still learning the foundational concepts, a greater emphasis can be placed on AI-directed learning. As students learn the foundational concepts and work on building up their practical skills, the focus should shift to AI-supported learning, where the student works with the AI tool as collaborators. And once students have mastered the practical skills and are cybersecurity professionals, they can be AI-empowered, with AI used as a tool to support them. The ability to rely on technological tools is critical to how scientists and engineers solve complex problems in the real world (Zhai, 2022).

In furtherance of this goal, it is important to accept and embrace generative AI as a tool. The more we encourage and shape its use in education, the better we can direct students to use it in the proper way as a learning tool. It is important to remember that AI cannot think for us and the development of critical thinking and practical skills is even more important as we will need to provide the elements that AI cannot provide.

References

- Al-Hawawreh, M., Aljuhani, A., & Jararweh, Y. (2023). Chatgpt for cybersecurity: practical applications, challenges, and future directions. *Cluster Computing*, 26, 3421-3436. [https://doi.org/10.1007/s10586-023-04124-5\(0123456789\(\),-volV\)\(0123456789,-\(\).volV\)](https://doi.org/10.1007/s10586-023-04124-5(0123456789(),-volV)(0123456789,-().volV))
- Becker, B., Denny, P., Finnie-Ansley, J., Luxton-Reilly, A., Prather, J., & Santos, E. (2023). Programming is Hard – Or at Least It Used to Be: Educational Opportunities and Challenges of AI Code Generation. *SIGCSE 2023: Proceedings of the 54th ACM Technical Symposium on Computer Science Education*, 500-506. <https://doi.org/10.1145/3545945.3569759>
- Dhoni, P. & Kumar, R. (2023). Synergizing Generative Artificial Intelligence and Cybersecurity: Roles of Generative Artificial Intelligence Entities, Companies, Agencies and Government in Enhancing Cybersecurity. *Journal of Global Research in Computer Sciences*, 14(3), 1-16. <https://doi.org/10.4172/2229-371X.14.3.005>
- Ellis, A. & Slade, E. (2023). A New Era of Learning: Considerations for ChatGPT as a Tool to Enhance Statistics and Data Science Education. *Journal of Statistics and Data Science Education*, 31(2), 128-133. <https://doi.org/10.1080/26939169.2023.2223609>
- Farrokhnia, M., Banihashem, S., Noroozi, O., & Wals, A. (2024). A SWOT analysis of ChatGPT: Implications for educational practice and research. *Innovations in Education and Teaching International*, 61(3), 460-474. <https://doi.org/10.1080/14703297.2023.2195846>

- Gartner, Inc. (2024, August 28). *Gartner Forecasts Global Information Security Spending to Grow 15% in 2025*. <https://www.gartner.com/en/newsroom/press-releases/2024-08-28-gartner-forecasts-global-information-security-spending-to-grow-15-percent-in-2025>
- Gasiba, T., Oguzhan, K., Kessba, I., Lechner, U., & Pinto-Albuquerque, M. (2023). I'm Sorry Dave, I'm Afraid I Can't Fix Your Code: On ChatGPT, CyberSecurity, and Secure Coding. *4th International Computer Programming Education Conference (ICPEC 2023)*, 2:1-2:12. <https://10.4230/OASICS.ICPEC.2023.2>
- Gupta, M., Akiri, C., Aryal, K., Parker, E., & Praharaj, L. (2023). From ChatGPT to ThreatGPT: Impact of Generative AI in Cybersecurity and Privacy. *IEEE Access*, 11, 80218-80245. <https://doi.org/10.1109/ACCESS.2023.3300381>
- He, Z., Nguyen, T., Rafatirad, S., & Sayadi, H. (2024). The AI Companion in Education: Analyzing the Pedagogical Potential of ChatGPT in Computer Science and Engineering. *2024 IEEE Global Engineering Education Conference (EDUCON)*, 1583-1592. <https://10.1109/EDUCON60312.2024.10578820>
- Joshi, I., Budhiraja, R., Dev, H., Kadia, J., Atallah, M., Mitra, S., Akolekar, H., & Kumar, D. (2024). ChatGPT in the Classroom: An Analysis of Its Strengths and Weaknesses for Solving Undergraduate Computer Science Questions. *SIGCSE 2024: Proceedings of the 55th ACM Technical Symposium on Computer Science Education*, 625-631. <https://doi.org/10.1145/3626252.3630803>
- Kabir, S., Udo-Imeh, D., Kou, B., & Zhang, T. (2024). Is Stack Overflow Obsolete? An Empirical Study of the Characteristics of ChatGPT Answers to Stack Overflow Questions. *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*, 935: 1-17. <https://doi.org/10.1145/3613904.364259>
- Kallonas, C., Piki, A., & Stavrou, E. (2024). Empowering Professionals: A Generative AI Approach to Personalized Cybersecurity Learning. *2024 IEEE Global Engineering Education Conference (EDUCON)*, 2295-2304. <https://doi.org/10.1109/EDUCON60312.2024.10578894>
- Leune, K. & Petrilli, S. (2017). Using Capture-the-Flag to Enhance the Effectiveness of Cybersecurity Education. *SIGITE '17: Proceedings of the 18th Annual Conference on Information Technology Education*, 47-52. <https://doi.org/10.1145/3125659.3125686>
- Lewis, M. (2022, December 26). What ChatGPT isn't the End of Programming. *Medium*. <https://drmarkclewis.medium.com/why-chatgpt-isnt-the-end-of-programming-c18ba352b99>
- Naval Postgraduate School. (n.d.). *Labainers*. Labainers – Center for Cybersecurity and Cyber Operations. <https://nps.edu/web/c3o/labainers>
- Nowrozy, R. & Jam, D. (2024). Embracing the Generative AI Revolution: Advancing Tertiary Education in Cybersecurity with GPT. <https://doi.org/10.48550/arXiv.2403.11402>
- OpenAI. (2025a). *ChatGPT* (February 13 version) [Large language model]. <https://chatgpt.com/share/67aeb703-685c-8011-a241-d238fc091d99>
- OpenAI. (2025b). *ChatGPT* (February 14 version) [Large language model]. <https://chatgpt.com/share/67af5c01-37c8-8011-ba24-8212f4e47d5f>
- OpenAI. (2025c). *ChatGPT* (February 14 version) [Large language model]. <https://chatgpt.com/share/67afa838->

241c-8011-b315-26d39cba49b4

- Ouyang, F. & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence*, 2, 100020. <https://doi.org/10.1016/j.caeai.2021.100020>
- Rogers, M., Hillberg, H., & Groves, C. (2024). Attitudes Towards the Use (and Misuse) of ChatGPT: A Preliminary Study. *SIGCSE 2024: Proceedings of the 55th ACM Technical Symposium on Computer Science Education*, 1147-1153. <https://doi.org/10.1145/3626252.3630784>
- Shardlow, M. & Latham, A. (Eds.) (2023). *ChatGPT in computing education: a policy whitepaper*. Council of Professors and Heads of Computing, UK. <https://e-space.mmu.ac.uk/633469/>
- Shepherd, C. (2025). Generative AI Misuse Potential in Cyber Security Education: A Case Study of a UK Degree Program. <https://doi.org/10.48550/arXiv.2501.12883>
- Simmons, R. & Park, J. (2024). Innovating Cybersecurity Education Through AI-augmented Teaching. *Proceedings of the 23rd European Conference on Cyber Warfare and Security (ECCWS 2024)*, 480-486. <https://doi.org/10.34190/eccws.23.1.2224>
- Toscano, J. (2023, April 20). Banning ChatGPT In Schools Is Like Banning Calculators In Math Class. *Forbes*. <https://www.forbes.com/sites/joetoscano1/2023/04/20/banning-chatgpt-in-schools-is-like-banning-calculators-in-math-class/>
- Warner, J. (2023, January 16). ChatGPT Both Is and Is Not Like a Calculator. *Inside Higher Ed*. <https://www.insidehighered.com/blogs/just-visiting/chatgpt-both-and-not-calculato>
- Welsh, M. (2023, January 1). The End of Programming. *Communications of the ACM*. <https://cacm.acm.org/opinion/the-end-of-programming/>
- Zhai, X. (2022, December 27). ChatGPT User Experience: Implications for Education. *SSRN*. <https://dx.doi.org/10.2139/ssrn.4312418>

Could Long-Term Covid-X Or Autoimmune Disorders Be Triggered Through the Mechanical Spreading of Covid-X -Virus Invades Bacteria Self-Inclusion-? It will be?

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Abstract: We wrote this opinion paper exclusively based on the author's experiences. Its main proposal concerns the possibility that a bacteria may have a couple of units of the coronavirus-X existing inside it. The reasoning is primarily physical, where several coronavirus-X units may fit inside a bacterial body. In such a situation, there is the possibility that units of coronavirus-x can be released into the human body, restarting the virus contamination -long-term coronavirus-X. It is the author's opinion that the virus could also live inside a bacteria.

Keywords: Covid-X, Physical Reasoning, Recontamination, Vaccines and Host, Living Beings, Antibiotic, Environment, Life Spam, Intelligence, Shielding, Immune System, Droplet Airborne

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Introduction

This opinion paper is based exclusively on the author's acquired experiences.

Suppose a bacteria contains a couple of units of coronavirus-X. In that case, units of coronavirus-X can be released into the human body, restarting the virus contamination—long-term coronavirus-X. (Balloni, 2023; Balloni, & Winter, 2020; Balloni, 2020).

A virus is a nonliving particle that is considered an infectious agent that requires a host for replication.

They infect all life forms, including animals, plants, bacteria, and archaea.

While bacteria are considered living organisms, viruses are considered organic structures -rather than living organisms-that interact with living organisms.

Bacteria reproduction happens through binary fission and conjugation. The virus invades the host cell, makes

copies of genetic material and proteins, and releases new particles by destroying the cell.

Bacteria cause localized infections. Viruses cause systemic infection. Antibiotics can prevent bacterial infections. Vaccines can prevent virus spread.

Yet, according to Panawala, 2017; A virus is a particle considered a nonliving form AND infectious agent. IT REQUIRES host forms, including animals, plants, bacteria, and archaea. Viruses are found in almost every ecosystem on the Earth. Thus, they are the most abundant biological entity type.

It is the author's opinion that the virus may also live inside a bacteria.

Additional details

From the explanation below (*) and rationalizing in terms of physical dimensions, we know (*) that a BACTERIA can CONTAIN up to 6 units of the coronavirus-X!

* See:

1. diameter of a bacteria: $1\ \mu\text{m}$ and $5\ \mu\text{m} = 1 \times 10^{-4}$ to 5×10^{-4} cm = 0.0001 - 0.0005 cm - average of 0.0003 cm
2. from the text below (*), we have that the diameter of the coronavirus = 0.00005 cm - therefore, inside a bacteria can be hosted -physically-, up to 6 units of coronavirus,
3. that is = $0.0003\ \text{cm} \text{-bacteria-} / 0.00005 \text{-corona virus-} = 3/0.5 = 30/5 = 6$ units of corona virus.

Suppose This Unit Can Be Contained or Confined Within the Living Bacteria. In That Case, It Is Possible That When the Bacteria Dies -or even before it dies, depending on the health aspects of the human being- The Virus Contained/Confined In It Can Become Active.

It is the author's opinion that the virus may also live inside a bacteria. Really? Here is the question for biophysicists, biochemists, and researchers in the medical field in general

*** Furthermore**

1. It is well known that the diameter of a hair strand is, on average, 100 microns = 100×10^{-4} cm = 0.01 cm
2. The diameter of the coronavirus is, on average, 450 nanometers (*) = 450×10^{-7} cm = 0.45×10^{-4} cm = 0.000045 cm (-which I ~approximate to 0.00005 cm)
3. The diameter of a droplet, that of air -in a sneeze is, on average, 5 microns = 5×10^{-4} cm = 0.0005 cm
Inside a sneeze droplet -breathing-, it may contain -if infected-: $(5 \times 10^{-4}) / (\sim 0.5 \times 10^{-4}) = 5/0.5 = 10$ units of the COVID-19 virus. A sneeze can spread up to 5 meters from the source!

Covid Lifetime (Panawala, 2017):

- . On stainless steel and plastic, the survival of the new coronavirus is 72 hours;
- . On cardboard, it survives for 24 hours;
- . On copper, for 4 hours;
- . In aerosol form -air-: 3 or more hours, and
- . In respiratory droplets -coughs, sneezes, or talks-. A person talking can emit thousands of droplets, remaining airborne for about 8–14 minutes.

Diameter of The Sars Predecessor

COVID family-: 60-220 nm. AVERAGE of 140 nanometers = 140×10^{-7} cm

Perspectives & Conclusion

The main message of this opinion paper is based uniquely on the author's acquired experiences. Its main proposal concerns the possibility that a bacteria may have a couple of units of the coronavirus-X existing inside it. The reasoning is primarily physical, where several coronavirus-X units may fit inside a bacterial body. In such a situation, there is the possibility that units of coronavirus-x can be released into the human body, restarting the virus contamination -long-term coronavirus-X.

The following reasoning seems logical: The current COVID-X (Balloni, 2023; Balloni, & Winter, 2020; Balloni, 2020). is about three times larger than its predecessor in the COVID family (item 5), and perhaps this is one of the reasons why it remains active for so long on surfaces (item 4), increasing its lethality as a function of time. This CORONA-X may live inside a human -or even not human- bacteria. After or even BEFORE this living being's health decreases, this virus -hidden inside the bacteria- may restart the recontamination process! Yet, if the bacteria die for any reason -antibiotic use- these dying bacteria favor the release of the CORONA-X to its environment -the human body or elsewhere.

Therefore, although the previous COVID was much more lethal, it had a shorter lifespan... it seems COVID-X has its intelligence and is looking for new ways to stay alive by self-protecting -shielding/hiding inside a bacteria.

In short, if you want to make a difference, try to live to the maximum aim: improving & boosting your immune system.

Finally, we do not have any evidence or plausibility that bacteria may harbor coronavirus-X units; however, no scientific research proves the contrary! However, **it is the author's opinion that the virus may also live inside a bacteria.** Really? Here is the question for biophysicists, biochemists, and researchers in the medical field in general.

So, this is a suggestion for a new scientific study to validate the proposal presented in this opinion paper.

References

- Balloni, A.J. (2023). *The Constant K and the Gaussian temporal evolution for COVID-19 & new wave of COVID-X*. South Florida Journal of Development, Miami, v.4, n.3. p.1665-1678, 2023. ISSN 2675-5459 - Retrieved from < <https://rb.gy/jwpst> > and last accessed on 10/02/2024.
- Balloni, A. J. & Winter, R. (2020). *The Constant K and the Gaussian Temporal Evolution for COVID-19*. In International Journal on Engineering, Science, and Technology (IJONEST), 2(1), 8-15. Retrieved from < <https://bit.ly/35gHvhS> > and last accessed on 10/02/2024.
- Balloni, A. J. (2020). PPT presentation at ILSET/2020: *The Constant K and the Gaussian Temporal Evolution for COVID-19*. International Journal on Engineering, Science, and Technology. Retrieved from < <https://rb.gy/9dvv2> > and last accessed April 4, 2024.
- Panawala, L. (2017). Difference Between Bacteria and Virus, The Biology Blog. Retrieved from https://www.researchgate.net/publication/314214838_Difference_Between_Bacteria_and_Virus -and last accessed on 0/07/2025.
- Ames, Hana. (2023). *How long does coronavirus last in the body, air, and food?* Medically reviewed by Joseph Vinetz, MD. In Medical News Today. Retrieved from <https://www.medicalnewstoday.com/articles/how-long-does-coronavirus-last> -and last accessed on 0/02/2014.

Does Students' Gender Affect Their Success in Economics Classes?

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Abstract: The effect of gender on student success and learning in economics classes has been investigated by several researchers; however, they have not reached a consensus. To provide new evidence, we investigate this issue by controlling more variables and using an ordered logit. Positive, significant correlations exist between grades and the following variables: GPA, number of hours worked, number of economic courses taken previously, SAT scores, expected grade at the beginning of the semester, number of hours spent studying for the class, number of attended classes, instructors' use of graphs and equations, and interest in the course. The results of the analysis showed that gender, type of economics course, SAT score, number of missed classes, instructor, and number of hours worked at a job were significant factors in success in economics courses. After controlling for factors such as number of hours worked, SAT scores, number of missed classes, instructors, junior status, number of economics courses taken, type of class, and interest in the class, results showed gender was a significant factor contributing to learning and success as measured by grades. Specifically, this result implies that female students are 1.39 times more likely to get a better grade compared to male students.

Key Words: Gender, Success, Economics classes, Teaching

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Introduction

Research has extensively explored factors influencing student performance and success in economics courses. Studies have investigated a wide array of variables, including student expectations (Ballard & Johnson, 2005; Owen, 2010), mathematical skills (Cohn et al., 1998; Cohn & Cohn, 2001; Hill & Stegner, 2003; Ballard & Johnson, 2004), instructor type and teaching methods (Watts & Bosshardt, 1991; Vachris, 1999; Colander, 2005; Goffe & Sosin, 2005; Laband & Piette, 1995; Robb & Robb, 1999; Porter & Serra, 2020), absenteeism (Romer, 1993; Durden & Ellis, 1995; Chan et al., 1997; Marburger, 2001; Cohn & Johnson, 2006), class size (McConnell & Sosin, 1984; Aries & Walker, 2004; Kara et al., 2021), student effort (Borg et al., 1989; Didia & Hasnat, 1998; Krohn & O'Connor, 2005; Lumsden & Scott, 1987; Park & Kerr, 1990), employment (Paul,

1982), seating location (Benedict & Hoag, 2004), personality type (Borg & Shapiro, 1996; Ziegert, 2000; Bisping & Eells, 2006), race (Stockly, 2009; Baderdm et al., 2021), and gender.

Investigations into the relationship between gender and student performance in economics have produced conflicting findings. Certain studies have demonstrated a trend of superior performance by male students (Siegfried, 1979; Lumsden & Scott, 1985; Lage & Treglia, 1996; Walstad & Robson, 1997; Borg & Stranahan, 2002; Gartner & Schneebaum, 2023), whereas others have identified no discernible gender effect (Williams et al., 1992; Greene, 1997; Saunders & Saunders, 1999; Ballard & Johnson, 2005). In a comprehensive analysis of previous research, Siegfried (1979) posited that gender-related differences, though not definitively proven, may originate in secondary education and extend into the collegiate level.

Building on Siegfried's 1979 research, numerous studies sought to clarify the gender gap in economics. Lumsden and Scott (1985) proposed that exam format influenced performance, suggesting females excelled in essay exams (averaging seven points higher) while males performed slightly better in multiple-choice tests (averaging four points higher), potentially due to a faster male learning rate. Lage and Treglia (1996) explored gender-inclusive teaching methods, which improved overall performance but also revealed persistent gender differences, with a notable increase in female achievement. Walstad and Robson (1997) analyzed multiple-choice results, attributing male students' advantage to sociocultural factors, cognitive variations, instructional methods, and the format of tests; they also used differential item functioning to identify gender differences. Borg and Stranahan (2002) further investigated the gender gap, confirming male outperformance and examining personality types (based on Kiersey-Bates temperaments) in macroeconomics principles. They concluded that gender impacts performance, but this effect varies based on personality.

Contrary to the research confirming gender disparities, several studies have found no significant gender effect in economics. For example, Williams et al. (1992), in their examination of intermediate macroeconomics, microeconomics, and statistics, reported neither consistent nor significant gender differences. While females outperformed males on essay sections of statistics exams, males did better on essay sections in macroeconomics and microeconomics. Similarly, females scored higher on numerical sections of microeconomics exams, but males outscored females on the numerical sections of macroeconomics, revealing no clear pattern. To test the hypothesis that females' superior verbal abilities might lead to better performance in verbal assessments, Greene (1997) analyzed his introductory macroeconomics classes over four years. He concluded that females did not outperform males in reading comprehension diagnostics, thus finding no support for the claim.

Saunders and Saunders (1999) explored whether the instructor's gender influenced gender disparities in economics. Analyzing data from introductory economics classes over six years (1984-1990) using multivariate analysis, they found no evidence that the instructor's gender explained any differences. Furthermore, Ballard and Johnson (2005) examined the relationship between grade expectations and gender, testing the idea that women might anticipate lower grades, potentially leading to self-fulfilling prophecies. While their research indicated

that positive grade expectations correlated with success, the gender effect on final grades was minimal and statistically insignificant among 1,462 students in introductory microeconomics taught by the same instructor.

To summarize, the existence of a gender gap in economics remains inconclusive due to conflicting research findings. While earlier studies suggested male students outperformed females, more recent research indicates no will conduct a further investigation, controlling for additional variables and employing an ordered logit model, as detailed in the following section.

Data and Methodology

This study utilized two data sets gathered from surveys administered during final exams at the University of North Dakota and West Chester University. At the University of North Dakota, all instructors of principles of economics classes distributed the survey, and all students taking the final exam completed it. The same survey was given to students at West Chester University during spring 2004 final exams, with all but one instructor participating. Student grades for these courses were also collected. A total of 744 responses were recorded for the survey's thirty-four questions.

To analyze the influence of gender on economics learning, we employ an ordered logit model, as our dependent variable (grades) is ranked from A to F (best to worst) (Greene, 2008). This approach differs from Park and Kerr (1990), who utilized a multinomial logit model, due to the inherent ordinal nature of the grade variable. To analyze the effect of gender, the following model is estimated:

$$\text{Grade} = \beta_0 + \beta_i (\text{class and student attributes}) + \text{error}, \quad i=1, \dots, 34. \quad (1)$$

The dependent variable, Grade, is the final grades that students received, A, B, C, D, and F in their principles of economics classes. Class and student attributes include GPA, gender, age, course, university housing, number of hours per week worked at a job, number of mathematics courses taken, number of economics courses taken, SAT score, expected grade at the beginning of the semester, expected grade at the end of the semester, number of hours per week spent studying for the class, number of missed classes, textbook rating by student, understanding when the instructor uses graphs to explain a topic, understanding when the instructor uses equations to explain a topic, interest in the course, whether to recommend the course to a friend, university, instructor (eight dummy variables for nine instructors), year of study (three dummy variable for sophomore, junior, and senior), and dummy variables for reasons for registering in the specific class.

Results

Table 1 provides an overview of the sample characteristics. The sample consisted of 64.4% male students (479) and 35.6% female students (265). The average grade achieved was 2.64 out of 4, which falls between a B and C,

and the mean GPA was about 2.98 (a B average). In terms of grade distribution, 22% of students received an A, 35% a B, 31% a C, and 12% a D or F. Due to the survey's administration in principles of economics classes, the student population primarily comprised first-year students (39%) and sophomores (around 40%), while the remaining 21% were juniors and seniors.

Table 1. Descriptive Statistics

| Variables | Mean | Std. Deviation |
|---|-------------|-----------------------|
| Grade | 2.64 | 1.011 |
| GPA | 2.98 | .567 |
| Age | 19.83 | 2.515 |
| Year in School : 1=Freshman 2=Sophomore 3=Junior 4=Senior | 1.86 | .850 |
| # of hours per week worked | 19.80 | 9.237 |
| University housing: 1= Yes, 0=No | .57 | .495 |
| Number of mathematics courses taken | 1.80 | 1.332 |
| Number of Economics courses taken | 1.65 | 1.978 |
| SAT Score | 1412.89 | 339.552 |
| Expected Grade at the beginning of the semester | 2.32 | .994 |
| Expected Grade at the end of the semester | 2.31 | .873 |
| # of hours per week spent on studying for the class | 2.79 | 2.143 |
| Number of missed classes | 4.57 | 4.247 |
| Textbook rating | 6.01 | 2.200 |
| Understanding when the instructor uses graphs to explain a topic | 7.10 | 2.275 |
| Understanding when the instructor uses equations to explain a topic | 7.17 | 2.202 |
| Interest in the course | 5.71 | 2.345 |
| Usefulness of the course | 6.26 | 2.273 |
| Whether to recommend the course | .73 | .447 |
| Preference: 1=50 minute class 0=75 minute class | .77 | .419 |
| Preference: 1=Morning class 0=Afternoon class | .58 | .494 |

Based on Table 1, a majority of students held jobs during the semester, working an average of 20 hours per week. The average student age was 20, with 90% being 21 years old or younger. Notably, 60% of respondents were enrolled in principles of microeconomics, while the remainder were in macroeconomics. Additionally, 57% resided in university housing. Half of the students had previously taken at least one math and one economics course. The average self-reported SAT score was 1413. As shown in the table, average expected grades remained relatively stable from the semester's start to its end, with changes primarily occurring at the lower and higher ends of the scale. For instance, while 25% initially expected a D, this decreased to 18% by the end. Similarly, those expecting an A dropped from 13% to 9%. On average, students reported studying less than three hours per week and missing five classes per semester, with 62% missing four or fewer classes.

On a scale of one to ten, with one being "very poor" and ten being "excellent," students rated the textbooks around a six. They indicated improved comprehension when instructors employed graphs and equations to illustrate concepts. While students' overall interest in the class was moderate (5.71), a majority (approximately 60%) perceived the course as useful, and 73% would recommend it to a friend.

Regarding class registration, 60% of students cited convenience as their primary reason, 24% reported conflicts with other classes, 3% mentioned work conflicts, and another 3% noted personal conflicts. Only 10% indicated the instructor's reputation influenced their decision. Additionally, 77% of students preferred a 50-minute class over a 75-minute one, and 58% favored morning classes over afternoon classes.

Table 2. Correlations with Grade

| | Correlation | Significance |
|---|--------------------|---------------------|
| GPA | 0.60** | (0.000) |
| Gender 1=Female, 0=Male | 0.04 | (0.253) |
| Age | 0.03 | (0.381) |
| University housing: 1= Yes, 0=No | 0.03 | (0.498) |
| # of hours per week worked at a job | -0.11* | (0.021) |
| Number of mathematics courses taken | 0.04 | (0.232) |
| Number of Economics courses taken | 0.10** | (0.007) |
| SAT Score | 0.23** | (0.000) |
| Expected Grade at the beginning of the semester | -0.16** | (0.000) |
| Expected Grade at the end of the semester | 0.03 | (0.496) |
| # of hours per week spent on studying for the class | -0.09* | (0.023) |
| Number of missed classes | -0.22** | (0.000) |
| Textbook rating | 0.03 | (0.477) |
| Understanding when the instructor uses graphs to explain a topic | 0.29** | (0.000) |
| Understanding when the instructor uses equations to explain a topic | 0.24** | (0.000) |
| Interest in the course | 0.18** | (0.000) |

*. Correlation is significant at the 0.05 level (2-tailed)

** . Correlation is significant at the 0.01 level (2-tailed)

Table 2 displays the correlations between grades and the independent variables. Significant positive correlations were found between grades and several variables, including GPA, hours worked per week, number of prior economics courses, SAT scores, initial expected grade, study hours per week, class attendance, instructors' use of graphs and equations, and course interest. Notably, an unexpected negative correlation was observed between grades and study hours per week. While seemingly counterintuitive, this finding aligns with results from previous research (Didia & Hasnat, 1998; Krohn & O'Connor, 2005).

Table 3. Ordered Logit Model Estimates

| Variable | Coefficient | Std. | |
|---|-------------|--------|----------|
| | | Error | P[Z >z] |
| Constant | 3.6443 | 0.2964 | 0.0000 |
| GPA | 0.0004 | 0.0004 | 0.2281 |
| Gender 1=Female, 0=Male | 0.3305 | 0.1473 | 0.0249 |
| Age | 0.0002 | 0.0004 | 0.6914 |
| Course 1=Macro, 0= Micro | 0.3797 | 0.1898 | 0.0454 |
| University housing: 1= Yes, 0=No | 0.0005 | 0.0007 | 0.5012 |
| # of hours per week worked at a job | -0.0003 | 0.0001 | 0.0310 |
| Number of mathematics courses taken | 0.0005 | 0.0004 | 0.2022 |
| Number of Economics courses taken | 0.0005 | 0.0003 | 0.0770 |
| SAT Score | 0.0003 | 0.0001 | 0.0005 |
| Expected Grade at the beginning of the semester | -0.0005 | 0.0009 | 0.5868 |
| Expected Grade at the end of the semester | 0.0008 | 0.0006 | 0.1695 |
| # of hours per week spent on studying for the class | -0.0004 | 0.0004 | 0.3592 |
| Number of missed classes | 0.0019 | 0.0005 | 0.0003 |
| Textbook rating | -0.0003 | 0.0011 | 0.7553 |
| Understanding when the instructor uses graphs to explain a topic | 0.0005 | 0.0014 | 0.7431 |
| Understanding when the instructor uses equations to explain a topic | -0.0007 | 0.0011 | 0.5445 |
| Interest in the course | -0.0026 | 0.0014 | 0.0670 |
| Whether to recommend the course | 0.0013 | 0.0005 | 0.0066 |
| University | 0.0924 | 0.3922 | 0.8137 |
| If Instructor 1=1, 0=Otherwise | -0.5125 | 0.3390 | 0.1306 |
| If Instructor 2=1, 0=Otherwise | -0.4077 | 0.6382 | 0.5229 |
| If Instructor 3=1, 0=Otherwise | -0.6704 | 0.4881 | 0.1696 |
| If Instructor 4=1, 0=Otherwise | 0.0800 | 0.4697 | 0.8647 |
| If Instructor 5=1, 0=Otherwise | -0.7418 | 0.5340 | 0.1648 |
| If Instructor 6=1, 0=Otherwise | -0.8432 | 0.3224 | 0.0089 |
| If Instructor 7=1, 0=Otherwise | -1.0306 | 0.6422 | 0.1085 |
| If Instructor 8=1, 0=Otherwise | 0.1801 | 0.5503 | 0.7434 |
| Sophomore =1, 0=Otherwise | -0.0278 | 0.1673 | 0.8679 |
| Junior =1, 0=Otherwise | 0.4720 | 0.2212 | 0.0328 |
| Senior=1, 0=Otherwise | 0.3663 | 0.3570 | 0.3049 |
| Reason for registration: Conflict w/ course | -0.1328 | 0.1789 | 0.4577 |
| Reason for registration: Conflict w/ work | -0.6161 | 0.4120 | 0.1348 |

| | | | |
|---|---------------------------------------|--------|--------|
| Reason for registration: Conflict w/ personal affairs | -0.5819 | 0.4413 | 0.1873 |
| Reason for registration: reputation of instructor | 0.0357 | 0.2289 | 0.8759 |
| Mu(1) | 1.8699 | 0.1075 | 0.0000 |
| Mu(2) | 3.6981 | 0.0809 | 0.0000 |
| Mu(3) | 5.3679 | 0.0976 | 0.0000 |
| Dependent Variable: Grades | | | |
| Log likelihood function= -978.1016 | Restricted log likelihood = -1030.485 | | |
| $\chi^2 = 104.7664$ | Degrees of freedom = 34 | | |

Tables 3 and 4 detail the ordered logit estimates for equation (1), with Table 3 demonstrating a satisfactory model fit based on the χ^2 and log-likelihood diagnostics. To assess the model's explanatory power, a likelihood ratio test was employed, as ordered logit models do not produce F-tests. The resulting χ^2 statistic of 104.77 (34 degrees of freedom) confirms a good fit and joint significance of the independent variables.

The cut-off points for grade categories (μ s) were all statistically significant. Z-values are reported in Table 3 in lieu of t-statistics, as is common in ordered logit analysis. Seven variables emerged as statistically significant at the 95% level: gender, course type, hours worked, SAT score, missed classes, course recommendation, and instructor number six. Moreover, prior economics courses and course interest were significant at the 90% level.

Interpreting the coefficients from an ordered logit model is more complex than with ordinary least squares. Each coefficient represents the log of the odds ratio. To determine the actual odds ratio, we must take the exponential of the coefficient ($e\beta$). For example, the gender coefficient is .3305, which translates to an odds ratio of 1.39. This means female students are 1.39 times more likely to achieve a higher grade compared to male students. Similarly, the odds ratios for being a junior, a macroeconomics student, a senior, and registering due to the instructor's reputation are 1.6, 1.5, 1.4, and 1.04, respectively.

Conclusions

Several factors, including hours worked, SAT score, the specific topics covered (microeconomics versus macroeconomics), and the number of missed classes, were found to have a substantial impact on student grades. By controlling for these variables, we investigated the effect of gender on performance in principles of economics courses and arrived at the following conclusions. The surveyed microeconomics and macroeconomics classes were primarily composed of male students. However, in contrast to numerous earlier studies that indicated male students excelled in economics, our results point to a different outcome. We observed a changing trend in the gender effect, with female students appearing to achieve greater success than male students in these courses.

References

- Aries, J.J. and Waller, D.M. (2004). Additional evidence on the relationship between class size and student performance. *Journal of Economic Education*, 341-329.
- Ballard, C.L. and Johnson, M.F. (2004). Basic math skills and performance in an introductory economics class. *Journal of Economic Education*, 3-23.
- Ballard, C.L. and Johnson, M.F. (2005). Gender, expectations, and grades in introductory microeconomics at a US university. *Feminist Economics*, 111, 95-122.
- Becker, W. E. and Watts, M. (1995). Teaching tools: Teaching methods in undergraduate economics. *American Economic Review*, 86(2), 448-453.
- Bedard, K., Dodd, J., and Lundberg, S. (2021). Can Positive Feedback Encourage Female and Minority Undergraduates into Economics? *AEA Papers and Proceedings*, 111. 128-132
- Benedict, M. E. and Hoag, J. (2004). Seating location in large lectures: Are seating preferences or location related to course performance? *Journal of Economic Education*, 215-231.
- Bisping, T. O. and Eells, J. B. (2006). Personality type as a determinant of student performance in introductory economics: macroeconomics vs. microeconomics. *Journal of Economics and Economic Education Research*, 3(28).
- Borg, M. O., Mason, P. M., and Shapiro, S. L. (1989). The case of effort variables in student performance. *Journal of Economic Education*, 20, 308-313.
- Borg, M.O. and Shapiro, S.L. (1996), Personality type and student performance in principles of economics. *Journal of Economic Education*, 3-25.
- Borg, M. O. and Stranahan, H. (2002). The effect of gender and race on student performance in principles of economics: The importance of personality type. *Applied Economics*, 34, 589-598.
- Chan, K. C; Shum, C. and Wright, D. J. (1997). Class attendance and student performance in principles of finance. *Financial Practice and Education*, 7, 58-65.
- Cohn, E., and Cohn, S. (1994). Graphs and learning in principles of economics. *AEA Paper and Proceedings* 197-200.
- Cohn, E, Cohn, S., Hult, R. E., Balch, D.C., and Bradley, (1998). The effects of mathematics background on student learning in principles of economics. *Journal of Education for Business*, 18-22.
- Cohn, E., Cohn, S., Balch, D. C., and Bradley, J. (2001). Do graphs promote learning in principles of economics? *Journal of Economic Education*, 299-310.
- Cohn, E. Cohn, S., Balch, D.C. and Bradley, J. (2004). The relation between student attitudes towards graphs and performance in economics. *The American Economist*, 48(2), 41-52.
- Cohn, E. and Johnson, E. (2006). Class attendance and performance in principles of economics. *Education Economics*, 14(2), 211-233.
- Colander, D. (2005). What economists teach and what economists do. *Journal of Economic Education*, 249-260.
- Didia D. and Hasnat, B. 1998. The determinants of performance in the university introductory finance course. *Financial Practice and Education*, 8, 102-107.

- Durden G. C. and Ellis, L. V. (1995). The effects of attendance on student learning in principles of economics. *AEA Papers and Proceedings*, 343-346.
- Gartner, H. L. and Schneebaum, A. (2023). An analysis of women's underrepresentation in undergraduate economics. *Review of Political Economy*, 35 (3). 593-613.
- Greene, B. (1997). Verbal abilities, gender, and the introductory economics course: A new look at an old assumption. *Journal of Economic Education*, 7, 13-30.
- Greene, W. H. (2008). *Econometric Analysis*. 6th Ed. Prentice Hall.
- Goffe, W. L. and Sosin, K. (2005). Teaching with technology: May you live in interesting times. *Journal of Economic Education*, 278-291.
- Hill, C.D. and Stegner. (2003). Which students benefit from graphs in a principle of economics class? *The American Economist*, 472, 69-77.
- Kara, E., Tonin, M. and Vlassopoulos, M. (2021). Class size effect in higher education: Differences in STEM and non-STEM fields. *Economics of Education Review*, 8, 21-13.
- Krohn, G. A. and O'Connor, C. M. (2005). Student effort and performance over the semester. *Journal of Economic Education*, 3-28.
- Laband D. N. and Piette, M. J. (1995). Better Learning from better management: How to improve the principles of economics course. Does who teach principles of economics matter? *AEA Papers and Proceedings*, 335- 338.
- Lage, M. J. and Treglia, M. (1996). The impact of integrating scholarship of women into introductory economics: Evidence from one institution. *Journal of Economic Education*, 6, 26-36.
- Lumsden, K. G. and Scott, A. (1987). The economics student reexamined: Male-female differences in comprehension, *Journal of Economic Education*, 18, 365-375.
- Marburger, DR. (2001). Absenteeism and undergraduate exam performance. *Journal of Economic Education* 322, 99-109.
- McConnell, C.R. and Sosin, K. (1984). Some determinants of student attitudes toward large classes. *Journal of Economic Education*, 181- 190.
- Owen, A. L. (2010). Grades, Gender, and Encouragement: A Regression Discontinuity Analysis. *Research In Economic Education*, 41 (3), 217-234
- Park, K. H. and Kerr, P. M. (1990). Determinants of academic performance: A multinomial logit approach. *Journal of Economic Education*, 21, 101-111.
- Paul, H. (1982). The impact of outside employment on student achievement in macroeconomic principles. *Journal of Economic Education*, 51-56.
- Porter, C. and Serra, D. ((2020) Gender Differences in the Choice of Major: The Importance of Female Role Models. *American Economic Journal: Applied Economics*, 12 (3), 226-254.
- Robb, R.E. and Robb, A. L. (1999). Gender and the study of economics: The role of gender of the instructor. *Journal of Economic Education*, 3-19.
- Romer, D., (1993). Do Students Go To Class? Should They? *Journal of Economic Perspectives*, 7 (3), 167-74
- Siegfried, J. J. (1979). Male-female Differences in Economic Education: A Survey. *Journal of Economic Education*, 10, 1-11.

- Stockly, S. K. (2009). Is a race a determinant of student performance in economics? *Review of Black Political Economy*, 36, 181-195.
- Vachris, M.A. (1999). Teaching principles of economics without “chalk and talk”: The experience of CNU online. *Journal of Economic Education*, 292-303.
- Saunders, K. T. and Saunders, P. (1999). The influence of instructor gender on learning and instructor ratings. *Atlantic Economic Journal*, 27, 4, 460-473.
- Walstad, W. B. and Robson, D. (1997). Differential item functioning and male-female differences on multiple-choice tests in economics, *Journal of Economic Education*, 155-171.
- Watts, M. and Bosshardt, W. (1991). How instructors make a difference: Panel data estimates from principles of economics courses. *The Review of Economics and Statistics*, 336-340.
- Williams, M. L., Waldauer, C. and Duggal, V. G. (1992). Gender differences in economic knowledge: a extension of the analysis. *Journal of Economic Education*, 219-231.
- Ziegert, A. (2000). The role of personality temperament and student learning in principles of economics, further evidence. *Journal of Economic Education*, 307-322.

Developments in the Study of the Microbiome: The Function of AI in Revealing Microbe-Host Interactions via Multi-Omics Integration

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Abstract: The epoch of big data, characterized by the escalating daily generation of data from diverse sources like medical devices, social media, mobile devices, and environmental sensors, offers novel prospects for analysis and information extraction. Advanced technologies are necessary for processing the complexity and diversity of these data. In this context, artificial intelligence (AI) and machine learning algorithms have emerged as advanced instruments capable of uncovering concealed patterns within data, facilitating the creation of tailored medicines such as enzymes, probiotics, and antibiotics. Artificial intelligence can link microbiome data with lifestyle information, yielding more precise therapy recommendations that assist in disease prevention and management. The human microbiome, comprising microbial populations, is essential for health maintenance via its interactions with the host. Alterations in the microbiome can precipitate illness development, underscoring the necessity for a more profound comprehension of the intricate interactions between microorganisms and their host. Recent research on the microbiome and its correlation with many diseases has led to significant progress in treatment methodologies. The application of modern technologies in this field may enable the development of personalized therapeutics and improve human quality of life; nonetheless, it requires careful deliberation and caution. The objective of this research is to enhance personalized medicine by utilizing microbiome data to develop drugs tailored to an individual's microbiota. This approach is anticipated to improve health outcomes and deliver more accurate treatments for a diverse range of conditions.

Keywords: Artificial Intelligence, Machine Learning, Human Microbiome, Multi-Omics, Microbiome

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Introduction

The microbiome is an interdisciplinary domain that includes agriculture, food science, biotechnology, bioeconomics, mathematics (comprising informatics, statistics, and modeling), plant pathology, and human

medicine. The term "microbiome" denotes the microorganisms, their habitat, and their interactions with the host, resulting in the establishment of distinct biological ecosystems. Microbiomes, as dynamic and interactive micro-ecosystems, have evolved alongside eukaryotic hosts and are critical to the host's survival and wellness.

Bacteria do not exist as isolated individuals but rather as vital components of a microbial community in the natural environment. Each of these microbial communities serves a specific role in the biological ecosystem. Furthermore, microbial habitats include a variety of abiotic and biotic elements that are necessary for the microbiome's survival and optimal function in conjunction with its host. Microbes have developed alongside the human body over time, making microbiomes critical for physiological activities such as metabolism, immunological responses, and behavior.

Microbiome symbiosis can result in a variety of diseases and health issues, including metabolic, immunological, and psychiatric abnormalities. Significant advances in microbiome research, particularly the use of DNA sequencing technology, have allowed for the discovery of new metabolic pathways, microbial adaptations and strains, as well as the monitoring of changes in microbial populations. These advancements make it possible to detect microorganisms in different anatomical places and conduct a more comprehensive analysis of the microbiome. However, efforts are being made to examine and combine this data with information from transcript omics, proteomics, metabolomics, and genomes. Because people and bugs have evolved together for a long time, microbiomes play a big role in how we behave, how our immune systems work, and how our bodies use food. Microbiome association can cause a lot of different illnesses, such as problems with the immune system, metabolism, and the mind. With the help of DNA sequencing technology, scientists have come a long way in their study of microbiomes. So far, this has helped us find new metabolic pathways, strains, and microbial changes. It has also helped us keep track of their communities. We can now find bacteria in more parts of the body and learn more about the human microbiome thanks to these changes. But people are working to look into this data and put it together with data from genes, transcript omics, proteomics, and metabolomics. We can use omics techniques like proteomics, metabolomics, and meta transcript omics to help people heal because they help us learn more about the structure and function of the microbiome. These studies help us find better ways to help each person by telling us more about the part microorganisms play in health and illness. The goal of this study is to make personalized medicine better by using microbiome data to make medicines that are specific to each person's microbiota. People will feel better about their health after taking these drugs. The innovations in this paper include the use of artificial intelligence and machine learning algorithms in microbiome research, which address the challenges of high-dimensional data, enabling more accurate analysis and prediction of health outcomes based on microbiome composition.

Also, the integration of omics (genomics, metabolomics, proteomics) technologies more comprehensively analyzes the dynamics of the microbiome and its impact on health, which can lead to better disease prediction and the development of personalized therapies. Better knowledge of the complex connections between the microbiome and the host also makes it possible to develop new therapeutic approaches, such treating or preventing diseases based on microbiome imbalance. In summary, this study demonstrates how emerging

technologies—specifically, artificial intelligence and omics—are transforming tailored medicine and microbiome research, which could lead to improvements in human health and illness management. This paper focuses on how artificial intelligence and machine learning can be used to analyze microbiome data, and generally considers the role of the human microbiome in health and disease. In the following sections of this article, we will discuss the details in different sections.

A Review of Microbiome Research and the Importance of Understanding Microbe-Host Interactions

Microbiomes serve as "multifunctional organs" for hosts by performing vital metabolic tasks and participating in a variety of processes required for growth, protection, health, and nourishment (McFall-Ngai et al., 2013). In turn, hosts provide microorganisms with resources, habitats, and modes of mobility (Obeng et al., 2021). Over the host's evolutionary past, these complex relationships have grown over time. During evolution, the microbiome and host can sometimes become so closely connected that they can work together as a single genetic unit (Fisher et al., 2017).

The microbiome can always have different parts. It's easier for new microbes to join or leave the microbial community, which makes it more functionally adaptable to changes in the environment (Bordenstein & Theis, 2015). The changes in the microbiome may have a direct effect on the health and efficiency of the host. Changing its make-up, especially during illness or microbial change, can mean big problems with how the body works.

Understanding the evolution and function of microbial communities necessitates an examination of the mechanisms that govern their formation and preservation. Microbial metabolites illustrate these pathways, as they experience significant changes in various diseases and microbiome disorders, including symbiosis. Consequently, an enhanced understanding of microbiome composition variability and its impact on host health should facilitate disease prediction and the formulation of personalized therapies (Shapira, 2016).

Recent breakthroughs in DNA sequencing technologies, especially next-generation sequencing (NGS), have transformed microbiome research. These technologies allow for the generation of billions of data points, facilitating a more exact and comprehensive analysis of the structure, function, linkages, and complexities of microbial ecosystems. Currently, we can monitor alterations in microbial communities and replicate the factors and situations that affect them (Abavisani et al., 2024).

These advancements facilitate the identification of new strains and the discovery of novel metabolic compounds, while also enabling the modeling and assessment of more accurate microbe-host interactions. A potent technique for examining microbiota dynamics, metagenomics has shown links between the composition of the microbiome and a variety of illnesses.

However, metagenomics data by themselves are unable to offer a comprehensive mechanistic explanation of health issues associated to the microbiome. So, it is important to use omics methods like metabolomics, proteomics, and metagenomics to add to metagenomics data and give a fuller picture of microbiome activity. These finds help us learn more about how microbes work and give us new ideas about how bacteria and hosts interact in many disease situations.

The Role of Artificial Intelligence (AI) in Advancing Microbiome Research

The Function of Artificial Intelligence (AI) in Progressing Microbiome Research Since the inception of the digital era, considerable progress has occurred in the computing capacities of artificial intelligence (AI). The phrase "machine learning" (ML) was initially coined by Arthur Samuel in 1959 (Samuel, 1959). Today, machine learning technologies have penetrated various sectors, facilitating everything from disease diagnosis and drug development to personalized therapeutic interventions and health pathway predictions.

This technology is utilized in data mining, computer vision, natural language processing, biometric identification, search engine optimization, medical diagnostics, business analytics, stock market forecasting, strategic gaming, and robotic operations. All these domains employ machine learning to enhance analysis and prediction accuracy. In the context of microbiomes, machine learning technologies can assist in evaluating model outcomes, identifying the biological significance of data, and conducting more precise research. Tools like permutation tests, feature ranking, and feature selection algorithms are especially critical in this domain. Microbiome data often present challenges for machine learning models due to their vast dimensions, complexity, and high noise levels.

These obstacles make it difficult to accurately predict and identify underlying trends. Features are evaluated or scored according to their value or relevance to the machine learning goal. Feature selection identifies a set of meaningful and distinct characteristics for a certain machine learning job by decreasing data dimensionality, noise, and redundancy. In addition to making microbiome data analysis more effective, these strategies may increase machine learning model performance, consistency, and interpretability (Abavisani et al., 2024).

The Microbiome and Its Complexities

Definition and Composition of the Microbiome

Turnbaugh and associates (*Turnbaugh & Gordon, 2009*) initially proposed the idea of the "core microbiome" in reference to the human microbiome. This phrase describes a group of microorganisms that are present and common in the majority of people. Venn diagrams were initially used to show the overlaps between these shared microbiomes. This idea aimed to streamline intricate studies of the human microbiome and investigate its connection to human health, especially in regard to obesity.

The idea of the core microbiome has been expanded to include food, plants, and animals due to notable developments in high-throughput sequencing. Since microorganisms are passed along through evolutionary processes, this core microbiome is necessary for the healthy operation of holobionts, or hosts and microbes as a single entity. This idea has gained a lot of attention lately in agricultural ecosystems, where it is applied to raise production, improve soil, and manage diseases.

Venn diagrams are a useful tool for identifying the core microbiome, but they frequently ignore other ecological factors because they are based on the classification of ecological traits. The emphasis has moved from straightforward identification to comprehending the ecological interactions within the core microbiome as a result of the development of omics technologies (sequencing biological data). To properly define the core microbiome, researchers have now put forth five conventional ecological parameters:

1. Membership (What microorganisms are there)?
2. Composition (What kinds of microorganisms are there)?
3. Phylogeny (What are the relationships amongst microbes in terms of evolution)?
4. Stability: How do microorganisms maintain their stability over time?
5. Connectivity: How can microorganisms communicate with the host and one another?

These methods are frequently employed to comprehend interactions between microbes and their hosts in ecosystems. Nevertheless, no single technique or strategy has been completely developed to describe the core microbiome since there is still disagreement regarding its precise definition.

Interaction Between Microbes and the Host

Symbiotic microbes are essential to the growth and maintenance of both human and animal health. Ninety percent of the millions of bacteria that live in the human body are found in the digestive tract. Type 2 diabetes, obesity, atherosclerosis, allergies, inflammatory bowel disease (IBD), and colorectal cancer are among the conditions that have been linked to gut microorganisms. The gut microbiota is therefore considered an essential component of the body's health and is often referred to as the "forgotten organ."

The microbes in the gut have a big impact on the host's metabolism. They break down and absorb indigestible carbohydrates from the food to supply this energy for body functions.

Common gut bacteria also function as pathogens, boosting the immune system, inducing antimicrobial defenses, and encouraging immune cell development.

Microbial communities in the gastrointestinal tracts of vertebrates consist of bacteria, viruses, archaea, and fungi. In humans, the gut houses millions of microbial cells, which outnumber the host's genes by more than 100 times and its cells by ten times. These microbes play a crucial role in regulating various disease processes and are mainly involved in regulating metabolism, pathogen resistance, and immune development.

The complexity of the symbiotic relationships between the microbiota and the host has evolved to maximize the benefits of a diverse microbiome, such as pathogen resistance and effective metabolism, while minimizing harmful effects such as symbiosis, microbial transfer, and inflammatory responses. To maintain host homeostasis, direct contact between the microbiota and epithelial cell surfaces must be limited and precisely regulated. These mechanisms include mucus layers, antimicrobial proteins, immunoglobulin A (IgA), and the regulation of co-growth among microbes.

The extensive genomic datasets from the Human Microbiome Project have provided unique insights into the composition, structure, and temporal dynamics of microbiomes. The next step in this field is to leverage this data for a better understanding of how the microbiota functions in health and disease (Kaetzel, 2014)

The Importance of the Microbiome in Health and Disease

Both animals and humans depend on symbiotic microorganisms to develop and preserve their health. The digestive tract is home to 90% of the millions of bacteria that inhabit the human body. Gut microorganisms have been linked to a number of illnesses, including type 2 diabetes, obesity, atherosclerosis, allergies, inflammatory bowel disease (IBD), and colorectal cancer, according to studies. Because of this, the gut microbiota is now considered an integral part of the body and is frequently referred to as the "forgotten organ."

The metabolism of the host is significantly influenced by gut microorganisms. By digesting and absorbing indigestible carbohydrates, they extract energy from meals and prepare it for the body's processes. The immune system is also strengthened by common gut microorganisms that function as pathogens, inducing antimicrobial defenses and immune cell development.

Vertebrate gastrointestinal systems are home to microbial populations that include bacteria, viruses, fungus, and archaea. Millions of microbial cells, which outnumber the host's cells and genes by a factor of ten and more than 100, respectively, reside in the human gut. These microorganisms are primarily engaged in controlling metabolism, pathogen resistance, and immunological development, and they are essential in controlling a number of disease processes.

In order to optimize the positive effects of a diversified microbiome, like pathogen resistance and efficient metabolism, and minimize negative effects, including symbiosis, microbial transmission, and inflammatory reactions, the microbiota and host have developed complicated symbiotic connections. The microbiota and epithelial cell surfaces must have limited and carefully controlled direct interaction in order to preserve host homeostasis. Mucus layers, antimicrobial proteins, immunoglobulin A (IgA), and the control of microbial co-growth are some examples of these systems.

Understanding the composition, structure, and temporal dynamics of microbiomes has been made possible by the Human Microbiome Project's vast genetic databases. In this field, the next step is to use this data to better

understand the role of the microbiota in both health and disease (Kaetzel, 2014).

The Role of Microbiota in Health and Illness

Numerous host variables, including as nutrition, cleanliness, exposure to the environment, use of antibiotics, and breastfeeding, affect the microbiota's makeup in the early stages of life. It is still difficult to assess any of these aspects' relative relevance, though. Some of the microbial elements and processes that influence the composition of the microbiota have recently been identified by research. Particularly in the early stages of life, the different oxygen levels in the gut are one of the primary factors that determine the composition of bacteria. These oxygen effects are correlated with the capacity of facultative anaerobic, obligatory anaerobic, and aerobic organisms to flourish.

Due to greater oxygen levels in the early stages of development, aerobic or facultative anaerobic bacteria (such Enterobacteriaceae, Enterococci, and Staphylococci) are usually the first to populate the gut. The fast consumption of oxygen by these bacteria, together with the production of metabolites, fosters the proliferation of anaerobic germs like Bacteroides, Clostridium, and Bifid bacterium. Thus, changes in the populations of facultative anaerobic and aerobic microorganisms are inversely linked with the microbiota's increasing complexity as the newborn gets older.

Diet, host components including mucus, and metabolites produced by microorganisms all have a big impact on the microbiota. These variables may have an impact on the composition of the microbiota depending on the unique dietary requirements of different commensals.

In recent years, there has been a growing recognition of the role that the microbiome plays in host health. The idea of the hologenome and photobiont has profoundly changed our understanding of the microbiome, especially with regard to treatment strategies. The host genome and its "second genome" (the microbiome), which is referred to as the hologenome, are thought to interact to form a "buffer" against several disruptions that impact host health. These interactions between the microbiome and the host are referred to as the "microbiota-epigenetic axis" or the "nutrient metabolism-host axis," in which the microbiota and its metabolites directly affect the host's epigenetic landscape by means of DNA methylation and histone modification (Wu et al., 2011). Additionally, the microbiome may influence medication regimens. The absence of a suitable microbiota to convert many prodrugs—which need metabolic conversion to become active—or the host's microbiome's degradation of them may keep them from becoming bioavailable. Antibiotic-resistant microorganisms, for instance, may proliferate as a result of NSAID use. Regional modifications may be necessary for microbiome-based therapeutics, as the diversity of microbial metabolic pathways may help to explain differences in medication reactions between people and groups.

Furthermore, the microbiota's influence on DNA methylation and histone acetylation patterns can affect transcriptional activity, illustrating the extent to which the microbiome can affect host health. Consequently, it is

essential to take into account the function of the microbiome in disease processes, particularly metabolic diseases such as obesity and their systemic effects on organ systems, in order to create effective therapeutic solutions (David et al., 2014).

Artificial Intelligence Applications in Microbiome Research 4.1 Artificial Intelligence's Function in Wide-Scale Microbiome Data Analysis

The Role of AI in Analyzing Extensive Microbiome Data

Today, technical advancements in high-throughput assays allow for the simultaneous processing of hundreds of thousands of test samples, yielding millions or even billions of data points across a range of biological domains. Complex disease pathogenesis includes several processes at several omics levels, including transcription of gene expression, epigenetic regulation of genes, proteomics, and metabolomics, all of which have an impact on disease endotypes. But up until now, these data have frequently been examined independently, leading to only approximations of the heredity of illnesses.

Furthermore, the majority of multi-omics analyses relies on traditional statistical techniques like logistic regression and support vector machines (SVMs), even if considerable attempts have been made to statistically integrate these kinds of data. These methods frequently fall short because they are unable to manage the enormous amount of data and capture the intricacy of the relationships between different data layers (Mirza et al., 2019; Wu et al., 2019; Olivier et al., 2019; Huang, Chaudhary, & Garmire, 2017; Subramanian et al., 2020).

Methods of Deep Learning and Machine Learning in Microbiome Research

High-throughput sequencing methods have recently made molecular-level imaging of biological material possible. In the context of precision medicine, integrating and analyzing multi-omics data is a crucial first step in gaining useful knowledge. Based on real-world techniques, this study is broken up into five major sections: factorization, feature extraction, clustering, network-based techniques, and deep learning. Here, we give a summary of the tools that are available in each area, with particular focus on the connections between these groups. Even though there are restrictions on how these data are integrated, the analysis shows how multi-omics datasets might be used to inform precision oncology research.

An outline of the AI-based steps: Trying to guess, sort, and put things together

Two types of AI, machine learning (ML) and deep learning (DL), are being used more and more in microbiome studies to help make sense of very difficult microbiome data. Some of the complicated and very different types of data that these programs look at the same time to make good predictions are proteomic, metabolomics, and genomic data. These methods are especially good at finding changes in the structure of the microbiome, guessing how bacteria will interact with the host, and looking at how the microbiome changes during disease.

Multi-Omics Integration: A Whole-System Perspective on Microbe-Host Interactions

Integrated multi-omics analysis is becoming more and more common. The structural and functional properties of microbial communities at different levels can be better understood thanks to these methods. Omics technologies give us more specific knowledge on the intricate relationships that exist between microorganisms and their hosts. In study areas including cancer, metabolic problems, and chronic diseases, these methods are particularly crucial.

Metabolomics, Proteomics, and Genomics

- **Genomics:** The goal of genomics is to collect and examine every gene and how it interacts with other genes in a living thing. In initiatives like the Human Genome Project, which aims to identify genetic diversity and polymorphisms, this use is very pertinent.
- **Proteomics:** This area of study examines all of the proteins found in cells and tissues, providing information on how cells react to illnesses. Key instruments in this discipline include methods such as protein interaction studies and mass spectrometry.
- **Metabolomics:** This study looks at metabolites and how they contribute to illness. Metabolomics examines fatty and amino acids to find connections between metabolites and genomes and disease pathways.

Multi-Omics

The word "omics" describes certain kinds of molecular data that offer a glimpse into a biological process. Proteomics, transcript omics, epigenetics, genomics, and other biological fields can provide these data. Simultaneously integrating this data can offer a systematic approach to comprehending biological problems. Using multi-omics data is essential for improving understanding of disease dynamics and making precise predictions, especially in the fields of medicine and cancer.

How Understanding Microbiome Dynamics Is Improved by Multi-Omics Integration

Analyzing various data types within a complete model is made possible by key multi-omics integration methodologies. These tactics include lowering the dimensionality of the data, utilizing different integration approaches, and analyzing complex data using machine learning models. This strategy's primary objective is to produce more precise forecasts of the dynamics of the microbiome and its interactions with the host.

Reducing Dimensionality to Integrate Multi-Omics Information

Large volumes of multi-omics data may now be produced for a variety of uses thanks to high-throughput next-generation sequencing. These data have transformed biomedical research by offering a more thorough understanding of biological systems and the molecular pathways behind the development of disease. Since deep learning algorithms can model nonlinear and hierarchical characteristics and are predictive, they have emerged

as one of the most promising approaches for analyzing multi-omics data (Wani & Raza, 2018).

Nevertheless, one of the most difficult tasks is still integrating and converting multi-omics data into useful insights. Understanding the intricate interactions between molecular levels is made easier by the clear trends that are emerging in biomedical research toward the combination of multi-omics data processing. Prevention, early diagnosis, tracking the course of a disease, interpreting patterns, and creating individualized treatment plans are all greatly enhanced by multi-omics data.

Machine Learning Techniques for the Analysis of Multi-Omics Data

In order to facilitate dimensionality reduction and establish links with clinical outcomes, machine learning techniques are very helpful when analyzing Omics datasets and clinical data in combination. Canonical Correlation Analysis (CCA) is helpful for investigating general relationships between two sets of variables, while simpler techniques like Principal Component Analysis (PCA) can be used to minimize the dimensions of data. Multiple Factor Analysis, Partial Least Squares (PLS) regression, and Sparse CCA are other integrated Omics frameworks (Picard et al., 2021).

A recent review found a number of software programs and tools for combining proteomic, metabolomics, and genomic data utilizing techniques such as empirical correlation analysis, biological network analysis, and pathway enrichment.

Categorization of Multi-Omics Data Integration Techniques

Four major categories can be used to group different approaches of integrating multi-omics data:

1. Graph-based Integration: This method uses visual aids like charts and similarity matrices to integrate data.
2. Dimensionality Reduction: In this case, data are combined by minimizing the dimensions that various Omics datasets have in common.
3. Statistical Integration: This approach integrates data using statistical approaches like Bayesian models.
4. Neural Networks: This method integrates multi-Omics data using artificial neural networks, especially deep learning.

An algorithm may belong to multiple categories but generally falls under one of these groups (Jain et al., 2021). Table 1 briefly summarizes the various methods of multi-Omics data integration.

Table 1. Multi-Omics data Integration Methods

| Category | Description |
|----------------|---|
| Graph-Based | Data integration using graphical representations such as charts or similarity matrices. |
| Dimensionality | Integration by reducing shared dimensions across different omics data. |

| | |
|-------------------|--|
| Reduction | |
| Statistical-Based | Statistical approaches, including Bayesian models, for data integration. |
| Neural Networks | Artificial neural networks and deep learning methods for multi-omics data integration. |

Multi-Omics Integration Tools and Platforms for Microbiome Research

A deeper understanding of microbiome-host interactions and their effects on human health and disorders can be gained in the field of biomedical research by merging different Omics data. To develop more accurate predictions about microbial behavior and host responses, these data can be quickly examined using sophisticated AI-based tools and platforms. Some of the AI models and applications in this field are covered here.

Models for Microbiome-Host Interaction Analysis Based on AI

Applying AI to Forecast Host Reactions and Microbial Behavior

A subfield of artificial intelligence called machine learning (ML) has emerged as a key instrument for forecasting intricate biological processes and mimicking human decision-making. Machine learning forecasts how microbes will behave and how hosts will react to different circumstances by analyzing past data and identifying trends.

Different kinds of machine learning exist, including:

- **Supervised Learning:** In this technique, algorithms forecast responses by using labeled data. Regression (for forecasting continuous values) and classification (for predicting categories) are two examples.
- **Unsupervised Learning:** In this case, algorithms assist in locating clusters or patterns in unlabeled data.
- **Reinforcement learning:** By using incentives and penalties to enhance judgments, this technique maximizes system performance.

Difficulties and Resolutions

Overfitting is a frequent problem in machine learning, where the model becomes very particular to the training dataset and is unable to predict new data accurately. Cross-validation and dimensionality reduction are two methods used to overcome issue.

Dimensionality reduction methods such as **Principal Component Analysis (PCA)**, **Linear Discriminant Analysis (LDA)**, and **t-SNE** help reduce data complexity, while cross-validation evaluates the model's diversity and predictive power when faced with new data (Huang, Lidbury, Thomas, Gooley, & Armstrong, 2025).

Examples of AI Models in Microbiome Research

Research on oral squamous cell carcinoma (OSCC): An investigation into the connection between the microbiome and OSCC, a type of oral cancer, studied how the microbial population in saliva may be systematically analyzed to identify certain patterns or "signatures" linked to OSCC's presence. These microbial profiles may offer crucial information about cancer in addition to possible markers for early detection or comprehension of the disease's progression. It talks about how alterations in the microbiome may be a sign of mouth cancer and a possible target for treatment, and it emphasizes the link between oral microbial populations and mouth cancer (Han et al., 2024).

enhancing the efficacy of immune checkpoint inhibitors (ICIs) in cancer treatment is discussed in the article. It demonstrates that immune responses against cancer can be strengthened by a healthy gut microbiota, and that the gut microbiota can significantly influence the immune system's response to immunotherapies. FMT, which uses healthy donor sources to try to rebuild the gut flora, may make ICIs more effective in patients who are not responding to traditional therapy. With careful donor screening and tailored therapy techniques, this approach may be a promising new strategy for treating cancers resistant to immunotherapies, while more study is required to optimize and understand its processes (Lin et al., 2025).

Deep Learning and Knowledge Graph Models: This article discusses the development of a deep learning model based on a microbiome knowledge graph designed to predict suitable microbes for specific hosts, such as humans or animals. By utilizing complex data and understanding the relationships between microbial features and host characteristics, this model can identify microbes that impact health or disease. The knowledge graph organizes extensive information on microbial genetics, metabolism, and functions alongside host features. This approach could be applied to improve microbiome-based therapies, personalized medicine, and drug development to enhance host-microbe interactions (Pan et al., 2024).

Machine Learning in Gut Microbiome Research: The article reviews machine learning platforms based on gut microbiomes and their therapeutic applications. It explains how deep learning can predict and enhance microbiome-related treatments. The study focuses on using machine learning models to analyze complex gut microbiome data, identify patterns linked to health and disease, and develop innovative therapeutic approaches. The article also explores the use of these techniques in personalized medicine, microbiome-based therapies, and improving drug efficacy (Malakar et al., 2024).

AI and Machine Learning Models in Microbiome Data Analysis

Artificial intelligence (AI) and machine learning algorithms can be very useful in analyzing complex microbiome data and in making more precise predictions regarding microbiome-host interactions and their therapeutic implications. By applying these strategies, we can improve immune responses, develop customized

therapies, and aid in the early detection of disease. However, further research and development are needed to optimize these models and their applications.

Machine Learning Models for the Identification and Prediction of Diseases

A significant advancement in the application of artificial intelligence for disease prediction is the creation of machine learning algorithms that facilitate the analysis of high-throughput sequencing data. These algorithms possess the capability to precisely identify microbial species and utilize this information to forecast the presence of pathogens. As an example, Oh and his colleagues created the Deep Micro model, which can correctly identify bacterial species from metagenomics data, even those that are hard to grow or not present in large amounts.

Artificial intelligence has shown a lot of promise in helping us understand the results of antimicrobial resistance tests. Artificial intelligence can find complex connections that might not be visible using traditional methods by using data that is easy to access. This can help doctors make better decisions.

Using Machine Learning to Analyze Complex Data

Especially when paired with metabolomics and transcriptomic data, microbiome data—particularly those obtained from metagenomics or Nano pore sequencing studies—are frequently extensive and intricate. To process and analyze these datasets efficiently, sophisticated computational tools are needed. This is where machine learning comes in, helping to accurately analyze complex data.

In this area, supervised learning techniques like Random Forest and Support Vector Machines (SVM) are quite effective. They are used to predict host characteristics and classify microbiome data. To find certain patterns and separate data into meaningful groupings, clustering techniques like K-means are also used. K-means clustering was employed in a well-known work by Knights and associates to distinguish different enter types in the human gut microbiota.

The Importance of Omics Techniques in Gut Microbiome Analysis

Human gut microbiome research depends critically on omics techniques like metagenomics, metabolomics, and transcriptomics. Every one of these methods examines several facets of the microbial population, therefore providing multidimensional understanding of its composition and purpose:

Transcript omics investigates variations in microbial gene expression; metagenomics helps analyze the genetic content of the microbiome; metabolomics counts compounds generated by bacteria. Given the volume and complexity of this data, machine learning techniques are crucial for integrating and comprehending it. These diverse datasets require complex algorithms that can identify patterns and intricate relationships, which aid in disease prediction and personalized treatment recommendations.

Disease Prediction and Personalized Medicine

Predicting disease using microbiome profiles is one of the most significant uses of artificial intelligence in personalized medicine. Based on differences in gut microbes, machine learning algorithms can predict diabetes, heart disease, and potentially cancer.

Machine learning, in particular, can leverage microbiome data to uncover health-related biomarkers and patterns, paving the way for microbiome-based therapeutics and personalized medicine. This strategy not only improves illness prevention but also encourages the development of personalized treatment programs for each patient.

Conclusion

Artificial intelligence (AI) and machine learning (ML) have opened up new possibilities for personalized treatment and disease prediction due to their ability to analyze complex data. These advancements, particularly in the field of microbiome research, enable us to predict disease and make better treatment choices by better understanding the intricate relationships between the microbiota and its host.

Future medical use of artificial intelligence is predicted to be more significant as new technologies and research are created. Its ability to transform healthcare by offering more precise diagnosis, tailored treatments, and a better knowledge of disease dynamics makes their great chances to improve human health outcomes.

References

- Abavisani, M., Foroushan, S. K., Ebadpour, N., & Sahebkar, A. (2024). Deciphering the gut microbiome: The revolution of artificial intelligence in microbiota analysis and intervention. *Current Research in Biotechnology*, 100211.
- David LA, et al. Diet rapidly and reproducibly alters the human gut microbiome. *Nature*. 2014;505(7484):559–63. doi: 10.1038/nature12820
- Fisher, R.M. et al. (2017) The evolution of host-symbiont dependence. *Nat. Commun.* 8, 15973 4. Bordenstein, S.R. and Theis, K.R. (2015)
- Han Z, Hu Y, Lin X, Cheng H, Dong B, Liu X, Wu B, Xu ZZ. Systematic analyses uncover robust salivary microbial signatures and host-microbiome perturbations in oral squamous cell carcinoma. *mSystems* 0:e01247-24. <https://doi.org/10.1128/msystems.01247-24>
- Host biology in light of the microbiome: ten principles of holobionts and hologenomes. *PLoS Biol.* 13, e1002226
- Huang S, Chaudhary K, Garmire LX. More is better: recent progress in multi-omics data integration methods. *Front Genet* 2017; 8:84

- Huang, K., Lidbury, B. A., Thomas, N., Gooley, P. R., & Armstrong, C. W. (2025). Machine learning and multi-omics in precision medicine for ME/CFS. *Journal of Translational Medicine*, 23(1), 68.
- Jain, M. S., Polanski, K., Conde, C. D., Chen, X., Park, J., Mamanova, L., ... & Teichmann, S. A. (2021). MultiMAP: dimensionality reduction and integration of multimodal data. *Genome biology*, 22, 1-26
- Jie Pan, Zhen Zhang, Ying Li, Jiaoyang Yu, Zhuhong You, Chenyu Li, Shixu Wang, Minghui Zhu, Fengzhi Ren, Xuexia Zhang, Yanmei Sun, Shiwei Wang, A microbial knowledge graph-based deep learning model for predicting candidate microbes for target hosts, *Briefings in Bioinformatics*, Volume 25, Issue 3, May 2024, bbae119
- Kaetzel CS. Cooperativity among secretory IgA, the polymeric immunoglobulin receptor, and the gut microbiota promotes host-microbial mutualism. *Immunol Lett*. 2014
- Lin, A., Jiang, A., Huang, L., Li, Y., Zhang, C., Zhu, L., ... Luo, P. (2025). From chaos to order: optimizing fecal microbiota transplantation for enhanced immune checkpoint inhibitors efficacy. *Gut Microbes*, 17(1). <https://doi.org/10.1080/19490976.2025.2452277>
- Malakar, Shilpa, Priya Sutaoney, Harishkumar Madhyastha, Kamal Shah, Nagendra Singh Chauhan, and Paromita Banerjee. "Understanding gut microbiome-based machine learning platforms: A review on therapeutic approaches using deep learning." *Chemical Biology & Drug Design* 103, no. 3 (2024): e14505.
- McFall-Ngai, M. et al. (2013) Animals in a bacterial world, a new imperative for the life sciences. *Proc. Natl. Acad. Sci.* 110, 3229–3236
- Mirza B, Wang W, Wang J, et al. Machine learning and integrative analysis of biomedical big data. *Genes (Basel)* 2019;10(2):87. 10.3390/genes10020087
- Obeng, N. et al. (2021) Evolution of microbiota–host associations: the microbe’s perspective. *Trends Microbiol.* 29, 779–787
- Olivier M, Asmis R, Hawkins GA, et al. The need for multi-omics biomarker signatures in precision medicine. *Int J Mol Sci* 2019. 10.3390/ijms20194781.
- Picard, M., Scott-Boyer, M. P., Bodein, A., Périn, O., & Droit, A. (2021). Integration strategies of multi-omics data for machine learning analysis. *Computational and Structural Biotechnology Journal*, 19, 3735-3746.
- Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. *IBM Journal of research and development*, 3(3), 210-229.
- Shapira, M. (2016) Gut microbiotas and host evolution: scaling up symbiosis. *Trends Ecol. Evol.* 31, 539–549
- Subramanian I, Verma S, Kumar S, et al. multi-omics data integration, interpretation, and its application. *Bioinform Biol Insights* 2020; 14:1177932219899051.
- Turnbaugh, P. J., & Gordon, J. I. (2009). The core gut microbiome, energy balance and obesity. *The Journal of physiology*, 587(17), 4153-4158.
- Wani N, Raza K. Integrative Approaches to Reconstruct Regulatory Networks From Multi-Omics Data: A Review of State-of-the-Art Methods. doi:10.20944/preprints201804.0352.v1
- Wu C, Zhou F, Ren J, et al. A selective review of multi-level omics data integration using variable selection. *High Throughput* 2019;8(1):4.

Wu GD, et al. Linking long-term dietary patterns with gut microbial enterotypes. *Science*. 2011;334(6052):105–8. doi: 10.1126/science.1208344



