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Las Vegas, USA

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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.

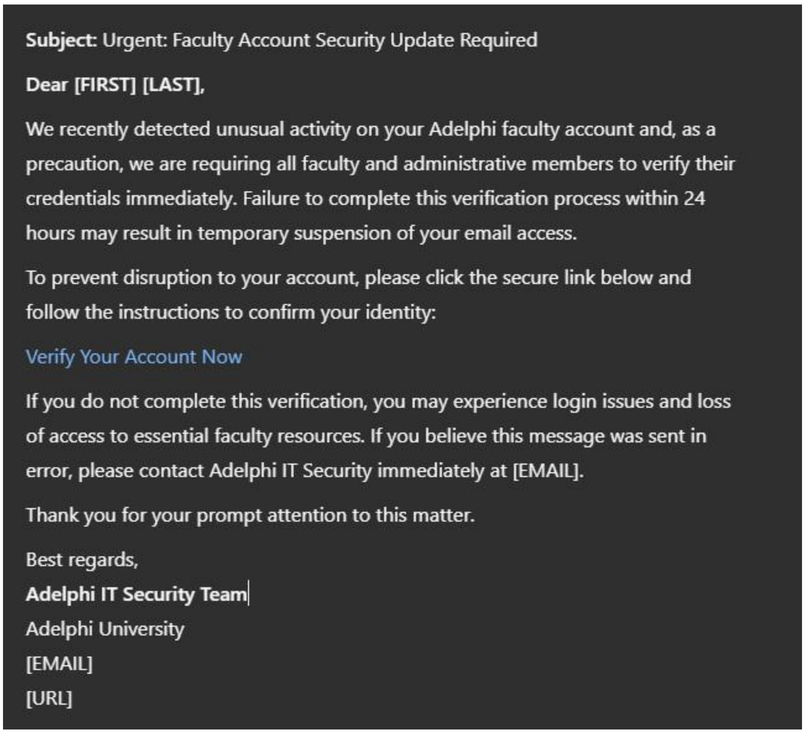
The third example is from a graduate-level course in cybersecurity techniques. The course is an advanced course that is an enhanced and accelerated version of the undergraduate computer and network security course. This course is offered in an online, asynchronous format over an eight-week period. Background 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):**

1. **Legitimate-looking branding:** The email uses professional design elements and a trusted company name ("ABC Electronics"), which makes it look real at first glance.
2. **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.
3. **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.
4. **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.
5. **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.
6. **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.

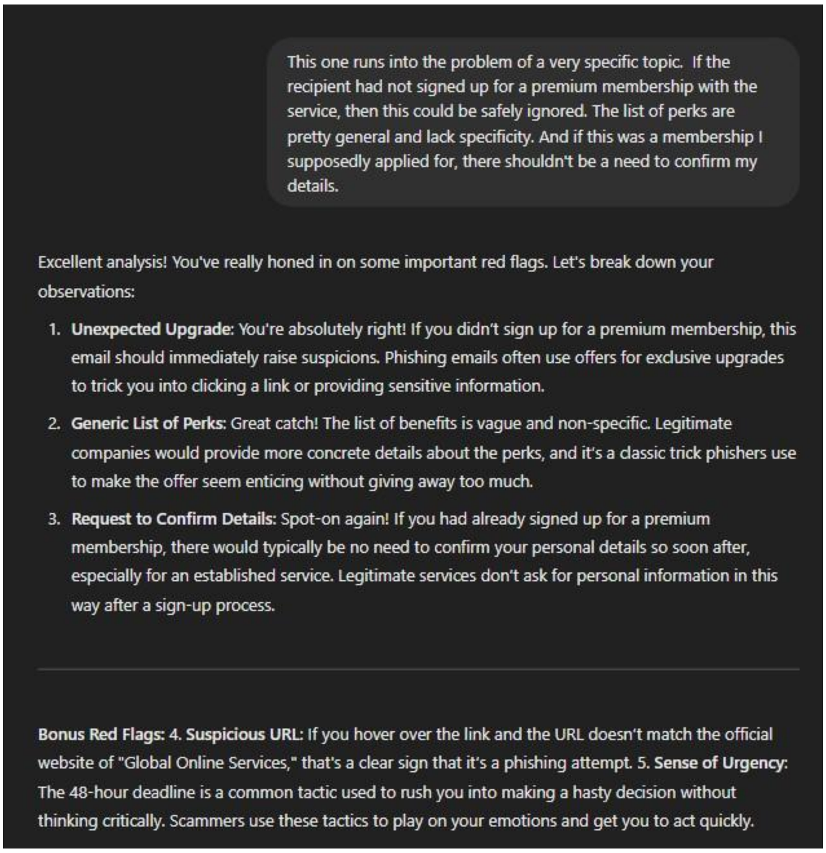



Figure 3. ChatGPT Evaluation of Phishing Quiz

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.

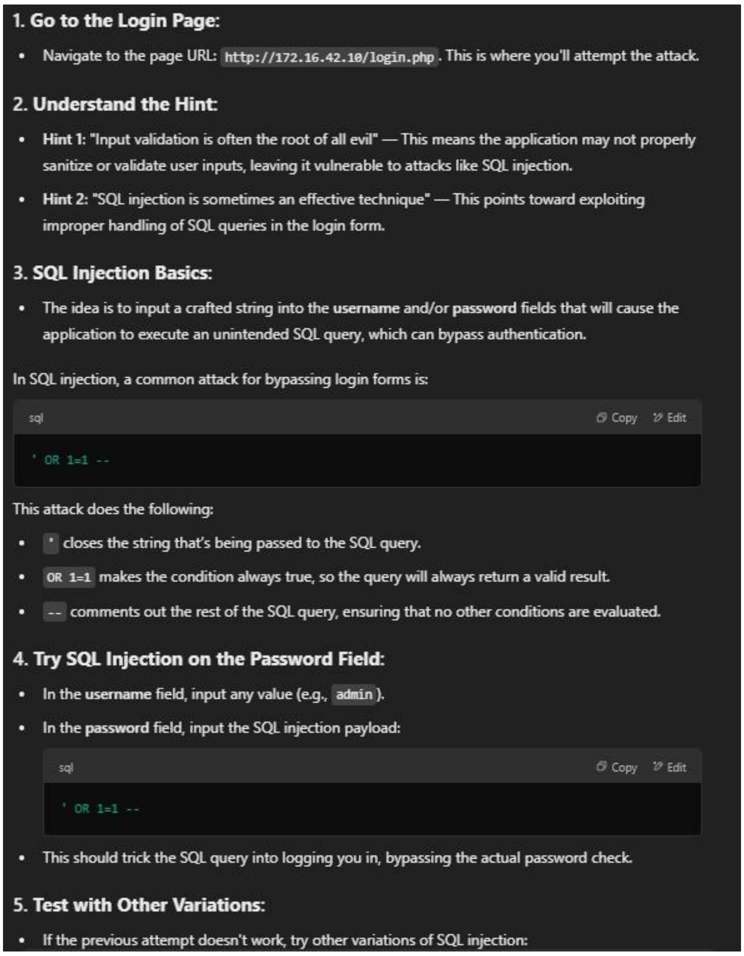
The challenges are grouped into three categories. The first category consists of five challenges where the students are directed to find flags simply by looking through the website, visiting the various pages, navigating the file directory, and inspecting the source of the webpages. The second category 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
' 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
' 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.

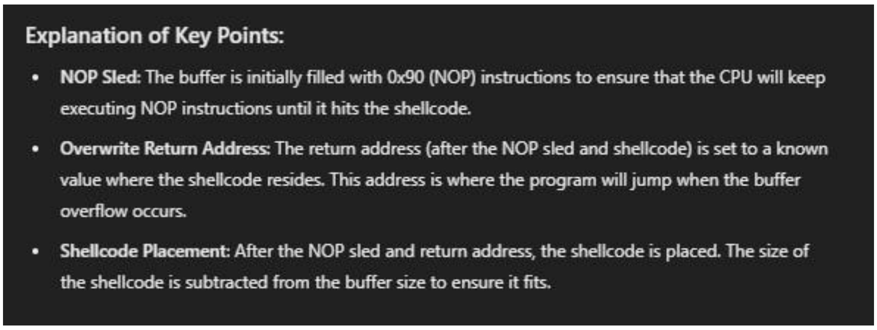
**Example 3: Buffer Overflow Exercise**

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.

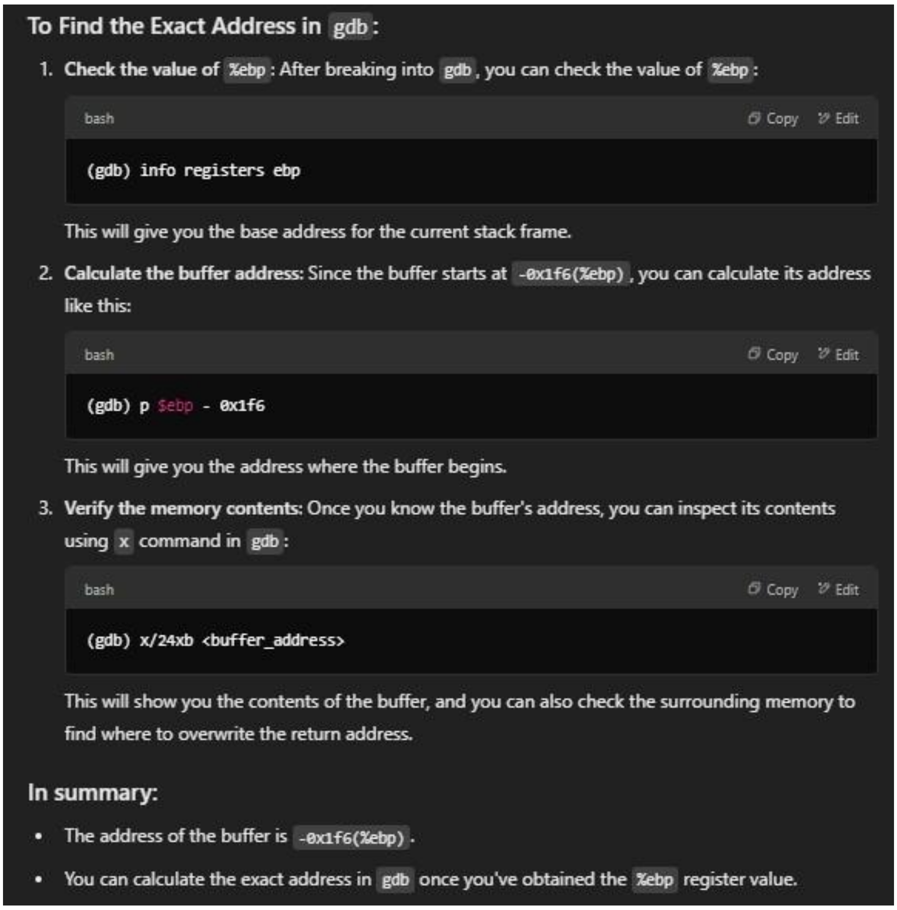


**Explanation of Key Points:**

- **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 Copy Edit
   ```
   (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 Copy Edit
   ```
   (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 Copy Edit
   ```
   (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.

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# 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 μm and 5 μm = $1x10^{-4}$ to $5x10^{-4}$ 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 cm -bacteria-/ 0.00005 -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 x $10^{-4}$ cm = 0.01 cm
2. The diameter of the coronavirus is, on average, 450 nanometers (*) = 450 x $10^{-7}$ cm = 0.45 x $10^{-4}$ 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 x $10^{-4}$ cm = 0.0005 cm
   Inside a sneeze droplet -breathing-, it may contain -if infected-: (5 $x10^{-4}$)/(~0.5 x $10^{-4}$) = 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 x $10^{-7}$ 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.

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# 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 & Sounders, 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:

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

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 | | | |
| | Restricted log likelihood = | | |
| Log likelihood function= -978.1016 | -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 $\chi^2$ 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 $\chi^2$ 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 (μs) 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 (eβ). 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.

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# 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, bio economics, 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 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 omens 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.

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# An Investigation of Middle School Students' Visual Literacy Regarding Environmental Problems

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**Abstract**: The purpose of this study is to examine middle school students' visual literacy regarding contemporary environmental problems. The sample of the study consisted of 187 eighth-grade students attending two middle schools in a small-scale city located in northeastern Türkiye. Conducted within a descriptive survey research design, the data were collected using a visual interpretation form developed to determine students' levels of knowledge and understanding of contemporary environmental issues. Students' abilities to interpret visuals related to environmental problems were analyzed descriptively using a classification that included the categories of "Full Understanding," "Partial Understanding," and "No Understanding/Blank." The findings revealed that the visual literacy levels of the majority of students regarding all environmental problems addressed in the study remained at the levels of "No Understanding" and "Partial Understanding." More specifically, the highest number of students demonstrated visual interpretations at the "Partial Understanding" level for the environmental problems of "Air Pollution" and "Melting of Glaciers," whereas their interpretations related to the "Degradation of Aquatic Environments" and the "Destruction of Natural Habitats" were predominantly categorized as "No Understanding." Overall, these findings indicate that the visual literacy levels of most students concerning environmental problems are generally weak.

**Keywords:** Environmental Problems, Visual Literacy, Middle School Students

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## Introduction

One of the greatest challenges facing societies in achieving a sustainable future is the reduction and resolution of contemporary environmental problems. Achieving this goal is only possible through the education of individuals who possess a strong sense of global citizenship and are committed to environmental sustainability (United Nations Environment Programme, 2022). Humanity is currently experiencing one of the most critical periods of transformation in its history and is confronted with unprecedented existential threats to survival (Skea et al., 2021). By jeopardizing the opportunities provided by diverse ecosystems, societies increasingly overlook the risk of ecological collapse, thereby weakening their capacity to build a sustainable and ecologically resilient future (Stroud et al., 2022).

Globally, millions of people are affected by water scarcity, while water pollution, droughts, floods, and the depletion of groundwater resources continue to generate severe negative impacts on human life (Srinivasan et al., 2012). Soil is not only being rapidly degraded but is also undergoing significant physical and chemical alterations (Fortner et al., 2016). Forest ecosystems today face multiple serious threats, among which deforestation stands out as a major driver of further environmental degradation (Myrtsidis, 2022). Enormous quantities of plastic waste result in severe consequences, including pollution, contamination of food chains, biodiversity loss, energy waste, and economic damage (Chow et al., 2017). Moreover, driven by fast fashion and intense competition, the fashion industry is becoming one of the most polluting industries worldwide (Sweeney, 2015). In the context of environmental education and sustainable living, numerous complex environmental issues are widely discussed, including climate change, global warming, melting glaciers, deforestation, biodiversity loss, air and water pollution, food waste, and ocean acidification (Gautam et al., 2021; Mogias et al., 2019; Nic Lughadha et al., 2020; Pozo-Muñoz et al., 2023; Varela et al., 2020). These issues collectively highlight humanity's complete dependence on nature and demonstrate that irresponsible human behavior toward this relationship can lead to consequences that threaten human existence itself.

One of the primary objectives of educational policies is to ensure that students understand the functioning of ecosystems and the environmental problems arising from human activities (Bayati, 2023; Riess et al., 2022). According to the United Nations Educational, Scientific and Cultural Organization, contemporary science education should be transformed to equip students with the knowledge, skills, and attitudes necessary to address and respond to environmental problems, particularly climate change. Visual representations play a crucial role in facilitating the understanding of many abstract and global concepts related to environmental issues, as they support the construction of accurate mental models. One of the ways to assess students' ability to think scientifically and critically about environmental problems is to examine how accurately they interpret visuals representing these issues. Students' capacity to correctly make sense of environmental visuals, analyze the messages conveyed through them, and relate these messages to scientific content constitutes a fundamental component of environmental literacy.

Environmental challenges are more pronounced in developing countries such as Türkiye. Therefore, the development of effective environmental education programs from the early stages of education requires identifying students' understandings of environmental problems and implementing programs that address their learning needs. In this regard, examining middle school students' visual literacy related to environmental problems enables the early identification of misconceptions, the evaluation of the effectiveness of instructional materials, and the development of evidence-based instructional approaches in environmental education. However, studies reporting middle school students' visual understanding of contemporary environmental problems remain limited. Moreover, in a developing country such as Türkiye, there is a clear need for comprehensive research to understand students' visual conceptions of environmental concerns that affect both their local geography and other regions of the world within the framework of global citizenship, as well as to identify their learning needs. Accordingly, this descriptive study aims to investigate the visual literacy related to environmental problems of eighth-grade middle school students attending schools in a small-scale city in northeastern Türkiye. In line with this aim, the following research question was addressed:

- What is the level of visual literacy of eighth-grade middle school students regarding environmental problems?

## Related Studies

The existing literature includes numerous studies examining students' knowledge and skills related to environmental problems (Boubonari et al., 2024; Gautam et al., 2021; Lam & Trott, 2022; Levrini et al., 2021; Pedrera et al., 2023; Xie et al., 2023; Yen et al., 2022). These studies predominantly investigate students' attitudes toward environmental issues using survey-based scales. However, only a limited number of studies have been conducted with middle school students, and investigations focusing on visual literacy remain insufficient. Most of the existing research has primarily aimed to examine students' perceptions of environmental problems through drawing-based methods. For instance, Liu et al. (2020) examined students' mental models of the marine environment and how these models relate to their perceptions of marine-related problems. Their findings revealed that students' mental models of the marine environment were generally partial and fragmented. Similarly, Avcı et al. (2013) explored eighth-grade middle school students' perceptions of environmental problems using different techniques and found that the themes reflected in students' drawings demonstrated limited diversity. In another study, Özcan and Demirel (2019) aimed to reveal the cognitive structures of sixth-, seventh-, and eighth-grade middle school students regarding environmental issues such as global warming, acid rain, the greenhouse effect, and the depletion of natural resources. The results indicated that the greenhouse effect was the environmental issue about which students had the least knowledge and the highest number of misconceptions.

## Method

### Research Design

This study aims to describe the current level of visual literacy regarding environmental problems among eighth-grade middle school students. Accordingly, the study was conducted as a descriptive research based on the survey model, one of the quantitative research approaches.

### Participants

In this study, a purposive sampling strategy was used to determine the sample. The research was conducted in two public middle schools located in the center of a small city in northeastern Turkey. The socioeconomic level of the students in the sample is generally medium or low, depending on their parents' occupations. The participants consisted of 187 eighth-grade students, including 91 girls (48.7%) and 96 boys (51.3%).

### Data Collection

The data of the study were collected in November 2024 through the administration of the "Environmental Problems Visual Literacy Form" in the selected schools, conducted face-to-face without disrupting the regular teaching–learning process. The form, developed by the researchers, consists of nine visual interpretation items addressing contemporary environmental problems. To ensure the validity of the instrument, a pilot study was conducted with 16 students who were not included in the main sample. Based on an examination of students' responses and their feedback regarding the clarity and readability of the visuals, necessary revisions were made to the draft form, and the instrument was finalized for use in the main implementation.

### Data Analysis

The quality of students' responses regarding what the visuals represented in the visual literacy form was analyzed descriptively using a classification developed by the researchers, consisting of the categories "Full Understanding (2)," "Partial Understanding (1)," and "No Understanding/Blank (3)" (Table 1). In this manner, all students' responses to the visual interpretation questions related to environmental problems were evaluated, and the percentages of students in each visual interpretation category were calculated and presented in graphical form. In addition, representative sample responses for each question were provided. To ensure the reliability of the analysis, in the first step, both researchers independently analyzed the data from 20% of the sample by evaluating all defined categories. The level of agreement between the researchers exceeded 90%. In the second step, discrepancies in the analyses were discussed until full consensus was reached. Subsequently, the remaining data were jointly analyzed by the researchers.

Table 1. Classification for Evaluating Responses to Visual Interpretation Question (VIQ) on Environmental Problems

| Theme of the image | Full Understanding | Partial Understanding | No Understanding/Blank |
|---|---|---|---|
| VIQ1: Degradation of soil structure (desertification) | Chemical pesticides and fertilizers used in agriculture, overgrazing, deforestation, urbanization, chemicals used for cleaning purposes, industrial waste, and extreme natural events such as water and wind erosion are among the various human activities that contribute to the degradation of soil structure, leading to desertification and the transformation of soil into poor-quality and unproductive land. | We have touched upon some of the fundamental concepts related to environmental issues. | An answer has been given that is meaningless or left blank. |

| Theme of the image | Full Understanding | Partial Understanding | No Understanding/Blank |
|---|---|---|---|
| VIQ2: Air pollution | Air pollution, one of the environmental issues caused by the gases released as a result of the combustion of fossil fuels used in areas such as manufacturing, heating, and transportation, is discussed. | | |
| VIQ3: Degradation of ocean, sea, lake, and river ecosystems | It is explained that waste and garbage generated by human activities accumulate in water sources such as oceans, seas, lakes, and rivers, causing the deterioration of water quality and destroying living organisms. | | |
| VIQ4: Melting of glaciers | The increase in the world's average temperature due to global warming is causing glaciers to melt. Consequently, the fresh water that enters the oceans as a result of glacial melting disrupts the salt balance of the oceans, negatively affecting marine ecosystems and causing sea levels to rise. It also means the loss of habitats for creatures living in the polar regions. | | |
| VIQ5: Flooding | It describes the flooding caused by continuous and heavy rain or melting snow. It causes great damage to residential areas and agricultural land in places where floods occur. | | |
| VIQ6: Destruction of forests | Forests not only purify the air but also provide a habitat for many living creatures. The destruction of forests will lead to increased air pollution and may cause the extinction of many species. | | |
| VIQ7: Destruction of life habitats | Urbanization, rapid population growth, expansion of agricultural land, and destruction of forests are causing habitats to disappear every day. This hinders activities such as feeding, sheltering, and reproduction, leading to the extinction of specie | | |
| VIQ8: Forest fires | Forest fires can occur as a result of human activities such as campfires, barbecues, cigarette butts, stubble burning, or glass and plastic bottles thrown into the environment, or due to natural causes such as lightning strikes, volcanic eruptions, or high temperatures. | | |
| VIQ9: Water pollution. | Chemical fertilizers, pesticides, sewage, oil spills, plastic waste, and garbage used in agriculture cause water pollution. Consequently, this damages the water ecosystem and leads to the depletion of clean water sources. | | |

## Results

### Results from the Analysis of Students' Visual Literacy Regarding Environmental Problems

The results of the analysis of the responses given by 8th grade students to visual interpretation questions (VIQ) related to environmental problems are presented (see Figure 1).

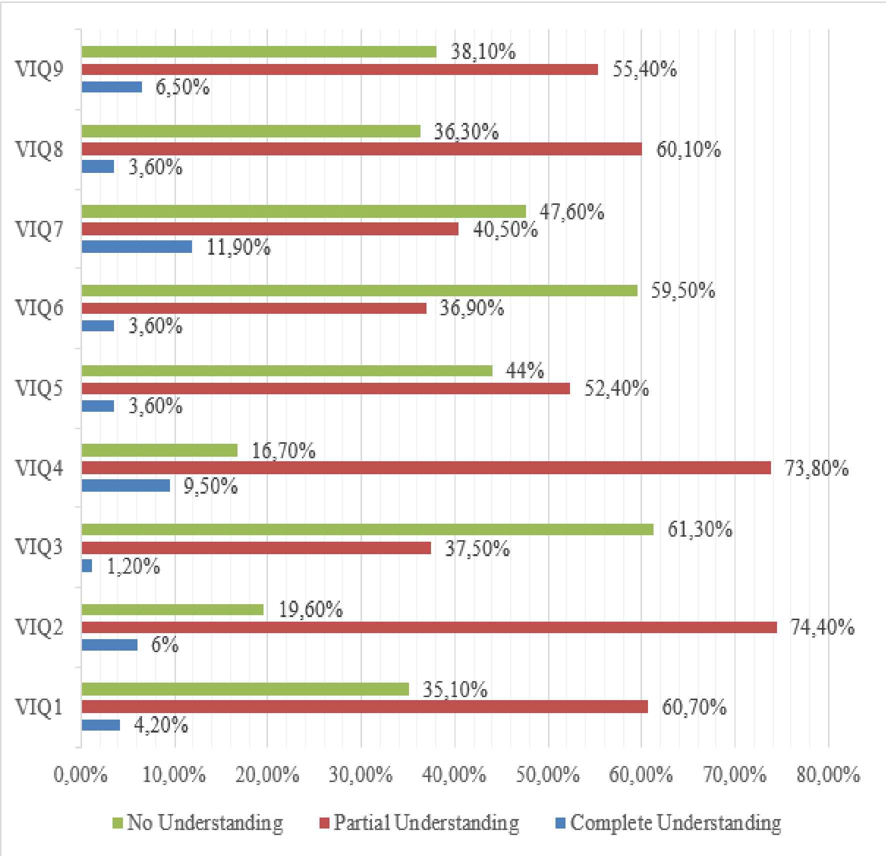
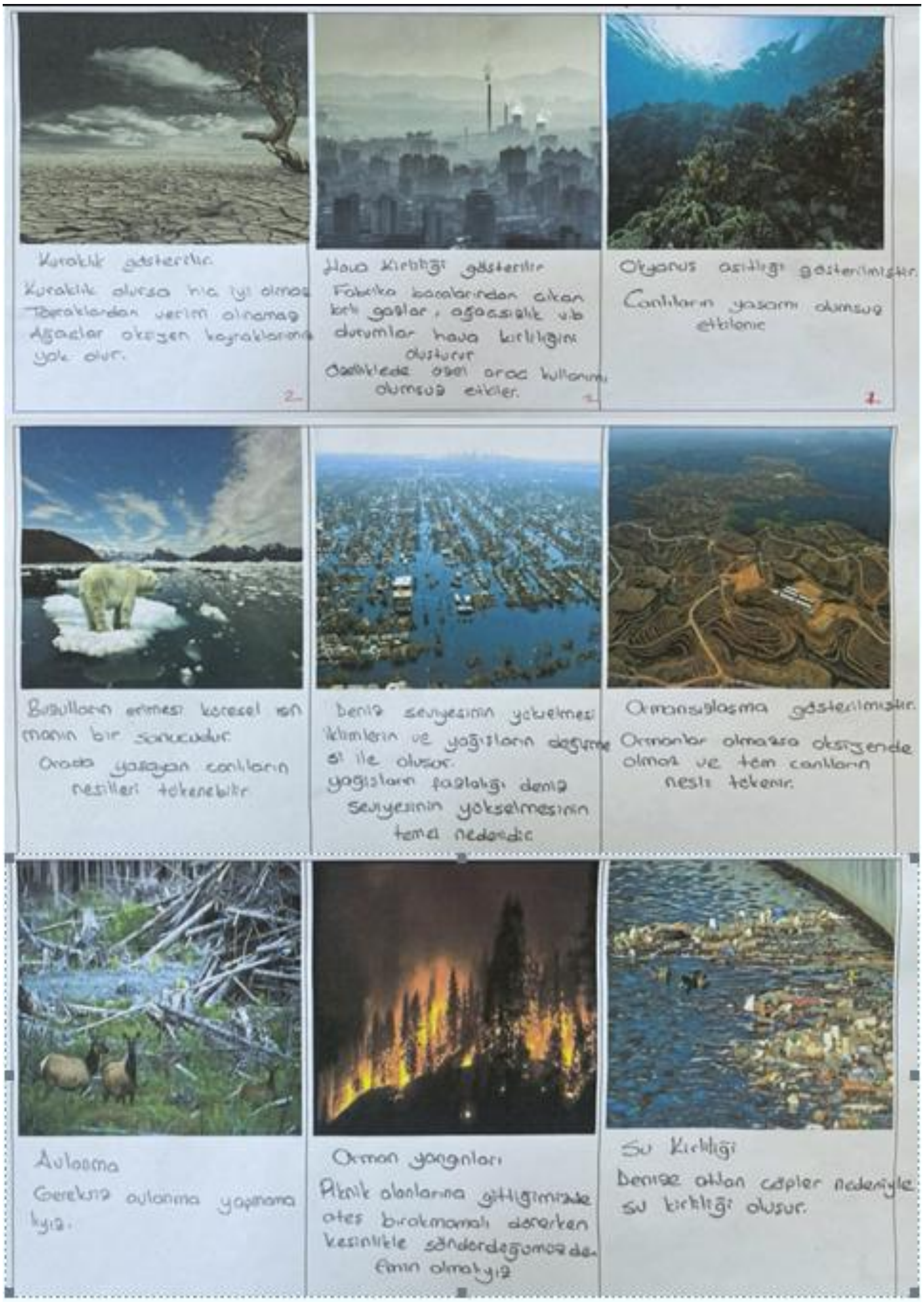



Figure 1. Results from the Analysis of Students' Responses to Visual Interpretation Question (VIQ) Related to Environmental Problems

The results regarding middle school students' visual literacy related to environmental problems are presented in Figure 1. An examination of the findings indicates that the majority of students remained at the "Partial Understanding" level across all visual interpretation categories related to the environmental problems addressed in the study. In addition, a substantial proportion of students were classified at the "No Understanding" level in all visual interpretation categories. In contrast, only a very small number of students demonstrated a "Full Understanding" of the visual representations of environmental problems. More specifically, the highest proportion of students demonstrated a "Partial Understanding" in the visual interpretation categories of "Air Pollution" (74.40%) and "Melting of Glaciers" (73.80%). Conversely, students' interpretations were predominantly categorized as "No Understanding" for the categories of "Degradation of Ocean–Sea–Lake–River Systems" (61.30%) and "Destruction of Natural Habitats" (47.60%). Overall, these results suggest that the visual literacy levels of the majority of students regarding environmental problems are weak. Moreover, the results indicate that most students experience difficulty in providing explanations for visual phenomena related to environmental problems. Examples of responses provided by an eighth-grade student coded as S21 to the visual interpretation questions are presented in Figure 2.



Note: The web addresses where the images related to environmental problems were obtained are provided in the references (URL1-URL9).

Figure 1. Examples of Students' Responses to Visual Interpretation Questions (VIQ) Related to Environmental Problems

## Discussion

This study aimed to examine the visual understanding of eighth-grade students attending two middle schools located in the city center of a small-scale city in northeastern Türkiye with regard to contemporary global environmental problems. In this context, the discussion and conclusions focus on students' visual literacy related to themes representing global warming, climate change, melting glaciers, sea level rise, ocean acidification, deforestation, species extinction, overfishing, soil degradation, water pollution, air pollution, plastic pollution, food waste, textile waste, flooding, and the destruction of natural habitats.

The results indicate that the majority of students' levels of visual interpretation related to environmental problems remained at the "No Understanding" and "Partial Understanding" levels. Specifically, the results revealed that the highest proportion of students demonstrated deficiencies in visual interpretation in the categories of "Air Pollution," "Melting of Glaciers," "Degradation of Ocean–Sea–Lake–River Systems," and "Destruction of Natural Habitats." This result suggests that visual elements are not sufficiently utilized in students' education to concretize and meaningfully support the understanding of environmental problems. Supporting this interpretation, Carducci et al. (2016) reported that the use of visual elements in air pollution education for middle school students led to improvements in knowledge, and those students receiving visual support demonstrated more effective understanding compared to those in a control group. Furthermore, many students' difficulties in making sense of environmental problems presented through visual media encountered in everyday life point to a broader lack of engagement with these issues. Overall, the results reveal that a considerable number of middle school students experience significant difficulty in interpreting environmental problems presented in visual form in depth and in accordance with their scientific meanings. Given that visual literacy is considered a critical component for understanding environmental sustainability from the early stages of education, these results indicate notable deficiencies in the implementation of environmental education within science courses for the examined sample. In line with this, Çakırlar Altuntaş and Levent Turan (2023) identified schools as the primary source of students' basic knowledge about environmental problems. In environmental education, visually supported augmented reality applications have also been observed to be more effective in helping students relate learned information to everyday life.

The results indicate that students' deficiencies in visual interpretation are particularly pronounced for environmental problems with global impacts, such as air pollution, melting glaciers, the degradation of ocean–sea–lake–river systems, and the destruction of natural habitats. Supporting these findings, Avargil and Saxena (2023) reported insufficient conceptual understanding of air pollution among 436 eighth-grade middle school students. Similarly, Sezen-Barrie et al. (2023) found that students experienced difficulties in constructing coherent explanatory models that adequately represent both the core ideas and the relationships between them when modeling the connection between climate change and ocean acidification. These difficulties may be attributed to students' perceptions of such environmental issues as abstract processes. In addition, students appear to have limited interaction with two-dimensional visual materials when attempting to make sense of visual content related to these environmental topics. Consequently, students' knowledge of environmental problems tends to remain at an abstract level, leading to superficial learning.

## Conclusion

This study indicate that the visual understanding of many middle school students regarding contemporary environmental problems is weak. Moreover, the findings suggest that these students have not been sufficiently engaged in pedagogical processes that effectively incorporate visual support related to environmental issues. Considering that students at the eighth-grade level are expected to develop higher-order cognitive skills in relation to environmental problems, these results highlight the need to redesign the science curriculum in Türkiye to more effectively integrate visual elements within the context of environmental education.

## Recommendations

This descriptive study on environmental problems acknowledges as a limitation the inclusion of students who are relatively less affected by environmental issues compared to other regions. At the same time, the study aims to encourage further research in both national and international contexts. Accordingly, future studies may be situated within broader contexts and integrated with diverse research methodologies. In addition, comparing students' visual understandings of environmental problems across different regions and contexts is likely to provide valuable contributions to the existing literature.

## Notes

This research was derived from the first author's master's thesis.

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# An Examination of Middle School Students' Understanding of the Relationship Between Natural Matter Cycles and Living Systems

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**Abstract**: The purpose of this study is to examine middle school students' understanding of the relationship between matter cycles and living systems. The study was conducted with 42 eighth-grade students attending three middle schools in a city located in the Central Black Sea region of Türkiye. This research employed a descriptive design within a qualitative research approach. Data were collected using an interview form. In the data analysis, students' views regarding the relationship between matter cycles and living systems were analyzed descriptively in line with predetermined themes and presented through frequencies. The findings indicate that many students failed to adequately construct various vital components of living systems across all matter cycles. This result suggests that students' learning of the life-related components of matter cycles in science courses remains at a superficial level and points to inadequacies in the pedagogical approaches used to teach these concepts.

**Keywords:** Matter Cycles, Living Organisms, Middle School Students, Science Education

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## Introduction

To address many of today's environmental challenges, students need to develop a deep understanding of the processes and relationships underlying complex ecosystems. In understanding life, students are expected to grasp how nature recycles and reuses matter through cyclical processes (Hoppe et al., 2020). Individuals' awareness of their environment is shaped by their knowledge of the interrelationships among environmental components and by their attitudes toward the environment (Al-Balushi & Al-Aamri, 2014). In this regard, international science education standards emphasize students' ability to analyze matter cycles and the interactions between biotic and abiotic components within ecosystems (Mambrey et al., 2022). Matter cycles (water, oxygen, carbon, and nitrogen) enable explanations of the hierarchical and complex organization of living systems at different levels (Lin & Hu, 2003). However, for many students, explaining macroscopic phenomena related to matter cycles in ecosystems using appropriate causal mechanisms, linking molecular-level elements and processes, and interpreting cyclical flows constitute significant learning difficulties.

Research on reasoning about ecosystems points to complex patterns arising from students' conceptual misconceptions and their difficulties in understanding domain-specific ecosystem representations (Düsing, 2025; Zangori & Forbes, 2015). Individuals often tend to explain complex phenomena using simple causal explanations, which hinders their recognition of interconnections and the complexity of processes within systems (Evagorou et al., 2009). This tendency is critically important in terms of making sense of matter cycles and developing ecological literacy (Düsing, 2025). Matter cycles are complex and interconnected phenomena that encompass ecological, physiological, biochemical, energetic, and autotrophic nutrition concepts. These complexities make it challenging for students to understand and accurately communicate these concepts. The complex nature of biological processes often leads to widespread misconceptions among students (Uke et al., 2024). Matter cycles represent a complex ecological topic and a fundamental process targeted for instruction at the middle school level. Previous research has examined students' understandings and perceptions of matter cycles to a limited extent (Arslan, 2023; Assarf & Orion, 2005, 2010; Astuti et al., 2024; Düsing et al., 2019).

Nature is a complex system in which the substances required for the survival of living organisms continuously circulate in cyclical patterns (Mambrey et al., 2022). These cycles enable the constant movement of essential elements, such as water, carbon, oxygen, and nitrogen, across ecosystems (Oh et al., 2021). Matter cycles involve a wide range of abstract and complex concepts for students (Arslan, 2023). In particular, a lack of understanding of the relationships among the components of these cycles may lead students to develop numerous conceptual misconceptions (Ugulu et al., 2015). In science education, comprehending and making sense of the relational networks, structural components, operational processes, and connections between complex systems such as matter cycles and living systems represent challenging cognitive processes (Pan & Liu, 2018). A detailed review of both international and national studies reveals a lack of research focusing on middle school students' understanding of the relationship between matter cycles and living systems. Therefore, there is a clear need for further investigation into students' understanding of these concepts during critical educational stages, such as middle school, when foundational knowledge of matter cycles is constructed. In this context, the purpose of the present study is to assess the extent to which middle school students understand the relationship between the water, carbon, oxygen, and nitrogen cycles in nature and living systems. Accordingly, the main research question guiding this study is: "What is the level of eighth-grade middle school students' understanding of the relationship between natural matter cycles and living systems?"

## Related Studies

A review of national and international studies on matter cycles (water, carbon, nitrogen, and oxygen) indicates that research has predominantly focused on high school and undergraduate student populations, rather than middle school students (Covitt et al., 2020; Düsing et al., 2019; Fackler & Capps, 2024; Hoppe et al., 2020; Soltis et al., 2021; You et al., 2021; Zangori et al., 2017). These studies have mainly examined conceptual misconceptions related to matter cycles, the modeling of cycles, and associated cognitive processes (Astuti et al., 2024; Damayanti et al., 2025; Hung et al., 2021; Vinisha & Ramadas, 2013). Only a limited number of studies have focused on middle school students.

Among these, Lin and Hu (2003) demonstrated that a large proportion of middle school students were unable to adequately recognize the relationships among different concepts related to energy flow and matter cycles. Arslan (2023) found that middle school students lacked sufficient knowledge of the fundamental concepts of matter cycles, which hindered their ability to construct scientific explanations. Moreover, students were found to rely primarily on non-scientific, superficial statements and to hold various misconceptions. In another study, Assarf and Orion (2005) reported that middle school students possessed incomplete mental models of the water cycle containing numerous misconceptions. Similarly, Barrutia et al. (2021) revealed that middle school students had insufficient understandings of precipitation mechanisms and their role within the water cycle. Furthermore, their findings indicated that none of the 246 participating students demonstrated an understanding of the cyclical dynamics of water, and that significant misconceptions related to condensation and evaporation were prevalent. Despite this body of research, no study was identified that specifically examines middle school students' conceptual understanding of the relationship between matter cycles and living systems.

## Method

### Research Design

This research is a descriptive study using a qualitative research approach that aims to reveal students' knowledge and understanding of the relationship between matter cycles and living organisms.

### Participants

The study involved 42 eighth-grade students attending three middle schools in the center of a medium-sized province in Turkey's Central Black Sea region. The schools from which the students in the study group were selected had similar socioeconomic characteristics. Of the students in the sample, 28 (67%) were female and 14 (34%) were male.

### Data Collection

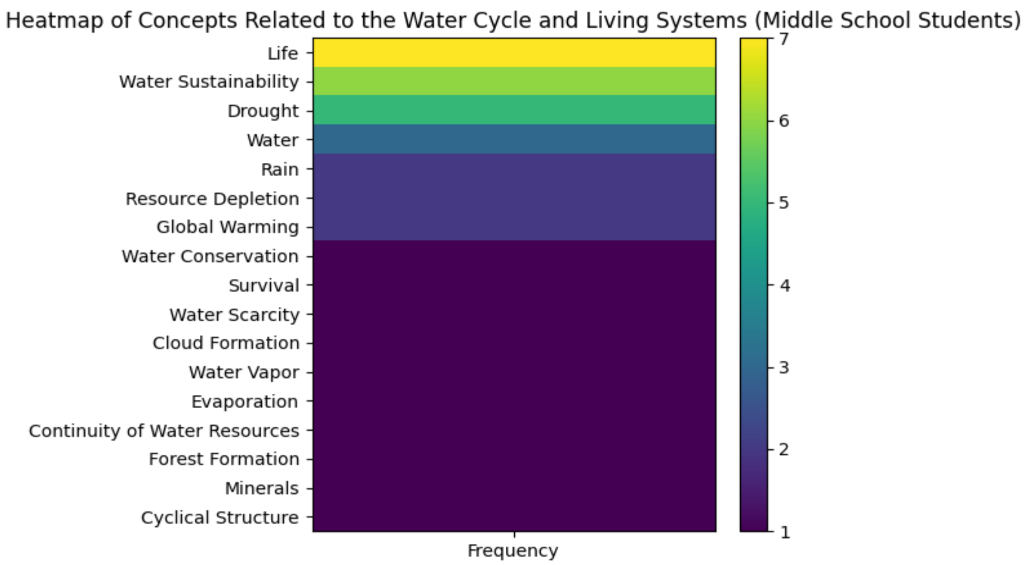
The data of the study were collected using an interview form consisting of open-ended questions designed to elicit students' understandings of the relationship between matter cycles and living systems. The draft interview form was reviewed by an academic specializing in environmental education and an experienced middle school science teacher who teaches this topic, and following the incorporation of their feedback and necessary revisions, the instrument was deemed valid for implementation. The interview form included four open-ended questions: (1) What is the relationship between the water cycle and life? (2) What is the relationship between the oxygen cycle and life? (3) What is the relationship between the carbon cycle and life? and (4) What is the relationship between the nitrogen cycle and life? The finalized data collection instrument was administered face-to-face by the researchers during time periods approved by school administrators and science teachers, without disrupting the regular instructional process. Ethical approval for the study was obtained from the provincial directorate of national education, and informed consent was secured from both the students and their parents.

### Data Analysis

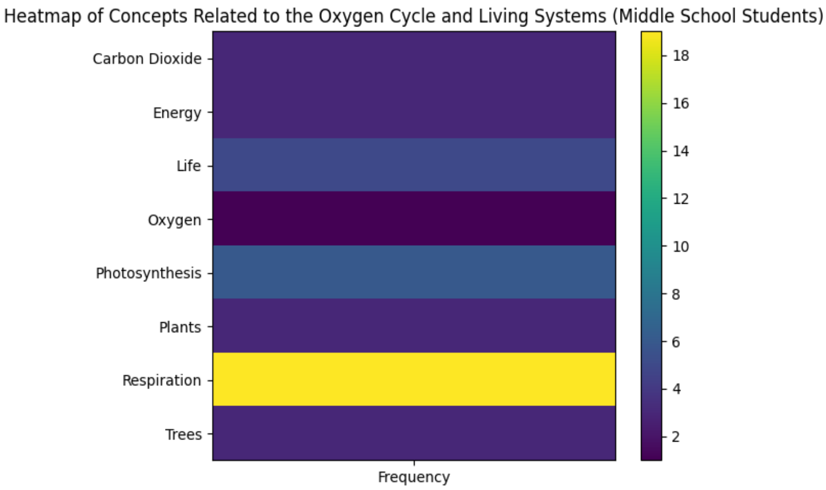
The data of the study were analyzed using the descriptive analysis method. For the analysis of the qualitative data obtained from the interview form, preliminary codes were first generated from each student's statements describing the relationship between living systems and the water, oxygen, carbon, and nitrogen cycles, respectively. Subsequently, similar codes within each cycle (e.g., precipitation/rainfall in the water cycle) were merged. For the main codes identified in each cycle, frequency-based heat maps were created. To ensure the reliability of the interview data, the researchers independently coded the responses of eight randomly selected students. The level of inter-coder agreement was assessed, and an agreement rate exceeding 90% was achieved, indicating a high level of coding reliability.

## Findings

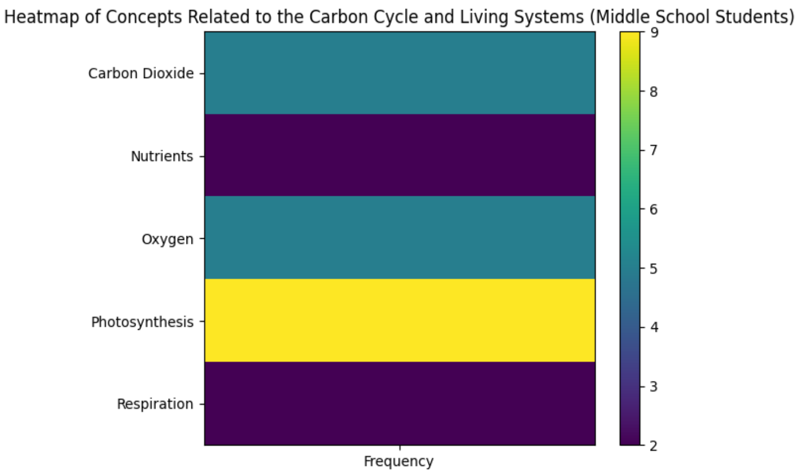
The heat maps illustrating the frequency distribution of the codes derived from the analysis of students' responses to the interview questions regarding the relationship between each matter cycle and living systems are presented in Figure 1.



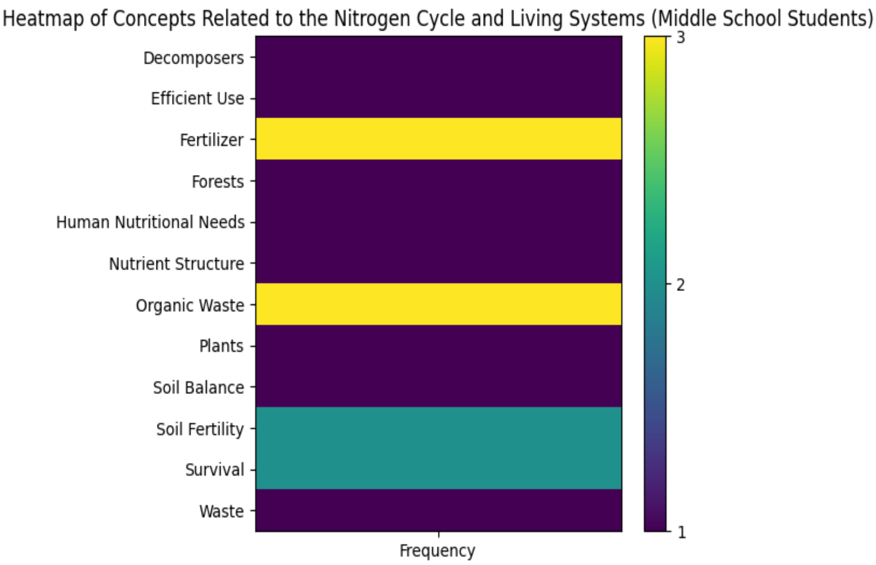

(a)




(b)



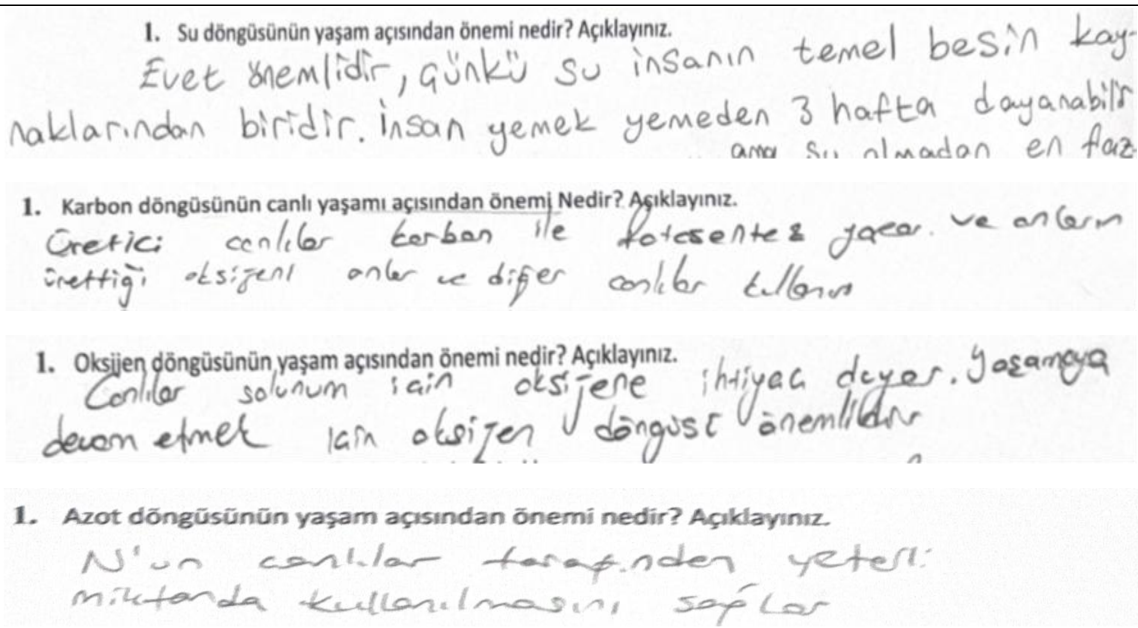

(c)




(d)

Figure 1. Heatmap of Concepts Related to the Matter Cycles and Living Systems

An examination of the heat maps reveals that, in students' views regarding the importance of the water cycle for living systems, the most frequently recurring codes were "life" (f = 7), "the continuity of water" (f = 5), and "drought" (f = 4). These findings indicate that students associate the water cycle with living systems primarily in terms of sustaining life, the continuity of water resources, environmental problems, and basic human needs. With respect to students' views on the relationship between the oxygen cycle and living systems, the most dominant code was "respiration" (f = 13). The prominence of this code suggests that students tend to perceive the oxygen cycle mainly as an individual life process. The codes "photosynthesis" (f = 6), "breathing" (f = 5), and "life" (f = 5) were also frequently emphasized, indicating that students recognize the importance of oxygen for living organisms. However, the less frequent mention of codes such as "carbon dioxide," "energy," and "plants" suggests that students made more limited connections to the systemic dimensions of the oxygen cycle. Regarding the carbon cycle, students most frequently associated it with the code "photosynthesis" (f = 9), indicating that they tend to conceptualize the carbon cycle primarily through plant-related processes. The codes "carbon dioxide" (f = 5) and "oxygen" (f = 5) were also reported relatively frequently, suggesting that students understand the carbon cycle mainly in terms of gas exchange. In contrast, concepts such as "respiration" and "breathing" appeared with lower frequencies, indicating that students have a limited understanding of the reciprocal exchange of matter among living organisms within the carbon cycle. In relation to the nitrogen cycle, the most frequently repeated codes were "living waste" (f = 3) and "fertilizer" (f = 3). This finding suggests that students primarily associate the nitrogen cycle with the return of waste to nature and agricultural production. In addition, the codes "soil fertility" (f = 2) and "survival" (f = 2) also occupied an important place in students' responses. Although these codes appeared with lower frequencies, they indicate that some students considered the nitrogen cycle in terms of ecosystem balance, nutrient structure, and human survival. Examples of student responses are shown in Figure 2.


1. Su döngüsünün yaşam açısından önemi nedir? Açıklayınız.
Evet önemlidir, çünkü su insanın temel besin kaynaklarından biridir. İnsan yemek yemeden 3 hafta dayanabilir ama su almadan en faz

1. Karbon döngüsünün canlı yaşamı açısından önemi Nedir? Açıklayınız.
Üretici canlılar karbon ile fotosentez yapar. ve onların ürettiği oksijeni onlar ve diğer canlılar kullanır

1. Oksijen döngüsünün yaşam açısından önemi nedir? Açıklayınız.
Canlılar solunum için oksijene ihtiyaç duyar. Yaşamaya devam etmek için oksijen döngüsü önemlidir

1. Azot döngüsünün yaşam açısından önemi nedir? Açıklayınız.
N'un canlılar tarafından yeterli miktarda kullanılmasını sağlar

Figure 2. Examples of Student Responses Regarding the Relationship Between Matter Cycles and Living Organisms

## Discussion

This study was conducted to reveal eighth-grade middle school students' understandings of the relationship between matter cycles and living systems. The findings highlight that students' understandings of the relationship between matter cycles and living systems are represented through specific codes. The results of the code-based heat map related to the relationship between the water cycle and living systems indicate that students most strongly associated this cycle with "life" and "the continuity of water." This finding suggests that students tend to conceptualize the importance of the water cycle for living systems primarily in terms of sustaining life and ensuring the continuity of water resources (Assarf & Orion, 2005). Moreover, the lower intensity of other codes reveals that students' understandings of the water cycle are concentrated around a limited set of concepts, while other life-related aspects of the cycle are associated to a more limited extent. These findings indicate that middle school students predominantly conceptualize the water cycle within the context of sustaining life through the continuity of water resources (Barrutia et al., 2021; Zangori et al., 2015).

The findings derived from the code-based heat map regarding the relationship between the oxygen cycle and living systems indicate that students prominently emphasized the code "respiration," suggesting that this cycle is predominantly structured around this concept in students' minds. The prominence of the respiration code reflects that students primarily encode the relationship between the oxygen cycle and life within the context of vital biological needs, revealing their awareness of the life-sustaining function of respiration. Although the code "photosynthesis" also emerged with notable frequency, concepts representing key elements of the oxygen cycle such as "carbon dioxide," "energy," "plants," and "oxygen" were represented at relatively low levels. This pattern suggests that while students are able to associate oxygen with the continuation of life, many struggle to conceptualize this relationship within a systematic, cyclical framework. Moreover, the findings indicate that students experience difficulty in addressing the oxygen cycle in terms of reciprocal matter transformations. In particular, the low frequency of the code "oxygen" implies that although students may recognize the term, they have difficulty constructing it meaningfully within a cyclical context. Overall, these findings reveal that students tend to interpret the relationship between the oxygen cycle and living systems primarily through a respiration-centered, human-focused perspective, while failing to adequately grasp the systemic interconnections among photosynthesis, carbon dioxide, and plants within the broader context of ecosystems and matter transformations (Astuti et al., 2024).

The findings from the code-based heat map regarding the relationship between the carbon cycle and living systems indicate that the code "photosynthesis" occupies a central position in students' mental representations of the carbon cycle. In addition, the codes "carbon dioxide" and "oxygen" were also frequently emphasized in students' descriptions. However, the low intensity of the codes "food" and "respiration" suggests that students experience difficulty in conceptualizing the carbon cycle as an ecosystem-based process. This pattern indicates that the relationship between the carbon cycle and living systems is not sufficiently constructed in terms of food chains, photosynthesis, and respiration. Furthermore, the findings reveal that students tend to conceptualize the carbon cycle primarily through gas exchange, while failing to adequately associate it with matter transfer among organisms and energy flow within ecosystems (Zangori et al., 2017).

The findings derived from the code-based heat map related to the nitrogen cycle indicate that students most frequently associated the codes "organic waste" and "fertilizer" with living systems. This pattern reveals that, in students' mental representations, the nitrogen cycle is primarily centered on the incorporation of various wastes into soil and agricultural practices. In addition, the presence of the codes "soil fertility" and "survival" in students' responses indicates an awareness of the importance of nitrogen for life. However, the low intensity of codes such as "decomposers" and "nutrient composition" suggests that students experience difficulty in conceptualizing the nitrogen cycle holistically, particularly in terms of microbial processes and food web dynamics. Overall, these findings demonstrate that students tend to conceptualize the nitrogen cycle mainly through the lenses of agriculture, soil, and fertilization, while possessing a limited understanding of the relationships involving microorganisms and decomposers, which constitute the core components of the cycle. This pattern points to insufficient emphasis on biogeochemical and ecosystem-based processes in the instruction of the nitrogen cycle (Townsend et al., 2007).

## Conclusion

Students' views regarding the importance of matter cycles for life indicate that they have not sufficiently constructed many vital components of these cycles in their mental representations. Furthermore, the majority of students demonstrated limited systems thinking with respect to matter cycles.

## Recommendations

Given the inadequacies in middle school students' knowledge structures regarding the relationship between matter cycles and living systems, it is recommended that science teachers employ models, diagrams, and visually supported activities that effectively illustrate the interactions among the living components of these cycles during the instructional process.

## Notes

This research was derived from the first author's master's thesis.

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