Engineering Educators Bringing the World Together
2025 ASEE Annual Conference & Exposition
Palais des congrès de Montréal, Montréal, QC • June 22–25, 2025
Paper ID #48324

Data-Driven Insights into AI-Powered Learning: Analyzing Student Interactions with AI-bot in Engineering Education

Abdulrahman AlRabah, University of Illinois at Urbana - Champaign

Abdulrahman AlRabah holds a Master of Science (M.S.) in Computer Science from the University of Illinois at Urbana-Champaign and a Bachelor of Science in Mechanical Engineering from California State University, Northridge. With experience across various industries, including oil and gas and co-founding a food & beverage company, his research focuses on optimizing AI feedback through customized large language models (LLMs) and improving computing courses to enhance both student learning and instructor experiences.

Zepei Li, University of Illinois at Urbana Champaign

Zepei Li is a Ph.D. student in Computer Science at the University of Illinois Urbana-Champaign (UIUC). He holds an M.S. and B.S. in Computer Science from UIUC. His research interests span AI in education, computer science education, and human-computer interaction. His previous work includes assessing student learning in database query languages and examining students' behaviors, attitudes, and beliefs toward generative AI in educational settings. He aims to enhance AI tools to better support educational applications.

Ms. Meredith Blumthal, University of Illinois at Urbana - Champaign

Meredith Blumthal has been in the field of international education for 15 years. As the Director for International Programs in Engineering (IPENG) at the University of Illinois, she leads the study abroad initiatives and programming for the college. Ms. Blumthal's team includes three study abroad advisors, a receptionist and peer advisors. Together the IPENG office provides study abroad advising, expertise, international exchanges, and cultural experiences in over 60 programs throughout 20 countries, with the goal of providing transformative learning experiences that empower students to develop global competency skills. Through partnerships with partner universities abroad, alumni, faculty, staff and student groups, Ms. Blumthal leads the IPENG team to provide study abroad advising, informational events, and class presentations. She works with the 12 engineering departments to develop and grow studying abroad programming with overseas partners to grow connections with universities, and facilitates the study abroad fair. Meredith is responsible for developing faculty-led programing an engagement within the College of Engineering. Her areas of expertise include ideation, program development, partner collaboration, faculty training and development, comprehensive program management, marketing and promotion, co-curricular development, study abroad advising, and student development.

Dr. Sotiria Koloutsou-Vakakis, University of Illinois Urbana-Champaign

Dr. Sotiria Koloutsou-Vakakis holds a Diploma in Surveying Engineering (National Technical University of Athens, Greece), a M.A. in Geography (University of California, Los Angeles), and M.S. and Ph.D. degrees in Environmental Engineering (University of Illinois Urbana-Champaign). She is a Senior Lecturer and Research Scientist in the Department of Civil and Environmental Engineering, at the University of Illinois Urbana-Champaign. Her main interests are in air quality, environmental policy, and supporting student learning and professional preparation.

Dr. Volodymyr Kindratenko, University of Illinois Urbana-Champaign

Volodymyr Kindratenko is the Director for the Center for Artificial Intelligence Innovation (CAII) at the National Center for Supercomputing Applications (NCSA). He is also an Adjunct Associate Professor in the Departments of Electrical and Computer Engineering and a Research Associate Professor in the Siebel School of Computing and Data Science. His research interests lie at the intersection of AI systems and applications, with a focus on generative AI solutions for science and education. His team is developing the uiuc.chat chatbot platform, which facilitates rapid knowledge distillation.

Prof. Tomasz Kozlowski, University of Illinois Urbana-Champaign

Dr. Tomasz Kozlowski is a Professor and Associate Head for the Undergraduate Programs in the Department of Nuclear, Plasma, and Radiological Engineering at the University of Illinois Urbana-Champaign. He received a Ph.D. in Nuclear Engineering from Purdue University in 2005. He has been an active member of the American Nuclear Society (since 1997) and the American Society for Engineering Education (since 2016). He is also a member of the OECD/NEA Nuclear Science Committee Working Party on Reactor Systems (NSC/WPRS) (since 2010) and is serving on the Scientific Board and Technical Committee of the OECD/NEA Benchmark for Uncertainty Analysis in Best-Estimate Modelling for Design, Operation and Safety Analysis of Light Water Reactors (LWR-UAM) (since 2008).

Dr. Abdussalam Alawini, University of Illinois Urbana - Champaign

Dr. Abdussalam Alawini is a teaching associate professor in the Department of Computer Science at the University of Illinois Urbana-Champaign. His research interests are broadly in database systems and computing education. In particular, he is interested in the application of AI technologies in facilitating active learning activities and improving online assessments. Dr. Alawini is very passionate about teaching. His teaching excellence is evidenced by his consistent recognition in the 'Excellent Teachers Ranked by their Students' over several semesters and his receipt of the 2024 Campus Excellence in Undergraduate Teaching award.

Data-Driven Insights into AI-Powered Learning: Analyzing Student Interactions with AI-bot in Engineering Education

Abstract

The integration of Generative Artificial Intelligence (GenAI) technologies in engineering education offers a significant opportunity to enhance students' learning experiences across various academic levels. To explore this potential, we analyzed data collected from AI-bot, a system that allows instructors to efficiently utilize a Large Language Model (LLM) on course-specific material. The resulting model is provided to students, enabling them to ask questions directly related to the course content. A unique aspect of the system is its ability to restrict responses strictly to the course material provided to it, ensuring accuracy and relevance. Additionally, the system logs all student prompts and model responses, creating a rich dataset for studying student interactions with the AI. Our findings show that some courses had more queries related to deeper conceptual understanding, while others focused more on logistical queries, highlighting the AI-bot's flexibility in meeting diverse student needs. This work contributes to the growing field of AI-assisted education by presenting a practical implementation of GenAI and offering insights into optimizing its application in academic settings.

1 Introduction

With recent advancements in machine learning, increasingly sophisticated and innovative technologies have been developed to address problems across various domains. One notable outcome of these advancements, which has gained significant popularity in recent years, is generative artificial intelligence (GenAI). GenAI encompasses techniques and tools, such as ChatGPT and Gemini, which are capable of generating meaningful text, images, audio, video, and other outputs based on training data [1]. This broad range of potential applications has encouraged people to explore diverse ways of using GenAI to help address various challenges. Education stands out as one of the most promising fields embracing AI's capabilities [2], [3].

One possible reason for the strong enthusiasm and research focus on AI in education is the paradoxical situation GenAI has created, offering unique advantages while also posing inherent drawbacks for students' learning. On one hand, it offers benefits such as personalized learning experiences [4], [5], [6], timely feedback [7], [8], enhanced information acquisition [8], and the potential to foster critical thinking [9]. On the other hand, it raises concerns among educators, including issues related to academic integrity [10], [11], [12] and questions about the effectiveness of GenAI in supporting students' learning [12], [13]. To effectively leverage GenAI in assisting students, it is essential to understand how students interact with this technology. While researchers have identified the potential benefits and drawbacks of GenAI in education, few studies have focused on how students interact with the technology. To address this gap, we provide a comprehensive analysis of students' interactions with a GenAI tool, referred to as AI-bot (a pseudonym used to maintain the anonymity of the actual system), across multiple engineering disciplines over the course of one semester. In this paper, we analyze data collected from AI-bot usage across five courses in different engineering disciplines, including Electrical and Computer Engineering, Computer Science, Civil and Environmental Engineering, Nuclear, Plasma & Radiological Engineering, and Agricultural and Consumer Economics. We seek to understand how students employ GenAI in their learning processes, focusing on the following research questions:

- RQ1: *What categories of questions do students seek help with using AI-bot?*
- RQ2: *What patterns appear in question types or student usage across different courses?*
- RQ3: *What types of assignments (e.g., written, programming, design) prompt students to use AI-bot most often?*
- RQ4: *Are there instances where students' use of AI-bot violates course policies, and if so, what are the characteristics of such violations?*

To address these research questions, we leveraged the detailed logs of student prompts and system responses provided by AI-bot. For RQ1 through RQ3, we employ a combination of qualitative and quantitative analyses to categorize student queries and identify usage patterns across courses. For RQ4, we compare student prompts with course syllabi and the university's student code to identify and characterize instances of potential policy violations. We use natural language processing (NLP) techniques to classify question types and patterns. This mixed-method approach will provide a comprehensive understanding of how students interact with the system and how it supports their learning. This study aims to provide insights into the role of AI-driven systems like AI-bot by investigating the different types of questions and their relevance in supporting student learning, while also addressing potential challenges and ethical considerations in their use.

2 Related Work

Researchers have shown a wide range of interests in the AI-in-education domain, with the majority focusing on the applications, impacts, and potential of GenAI in education [2]. Studies explore the effects GenAI may have on academic practices and how it could shape the way individuals participate in academic activities and achieve educational outcomes. For example, Oguz et al. and Kasneci et al. examined the effectiveness of tools like ChatGPT as educational aids in personalizing learning [14], [15]. Abedi et al. investigated the integration of Large Language Models (LLMs) and chatbots in graduate engineering education, highlighting their potential to enhance self-paced learning, provide instant feedback, and reduce instructor workload [16]. Alasadi and Carlos, as well as Baidoo-Anu and Ansah, discussed the potential benefits of GenAI in education, such as personalized tutoring and real-time feedback and assessment, alongside its drawbacks, including a lack of human interaction and biases in training data [7], [17]. In addition to this topic, researchers have explored other topics, such as ethical implications [18] and risks of GenAI [19], students' perspectives and experiences regarding with these tools [20], as well as both institutional and individual adoption [21], [2].

Despite the wide range of focus and the increasing number of studies related to AI in education, few have examined users' interactions with GenAI or sought to understand students' behaviors when using these tools. Related studies have primarily focused on designing AI tools to assist students' learning in specific ways and on evaluating and improving these tools. For example, Gabbay and Cohen developed a framework for LLMs to complement automated test-based feedback in programming courses, evaluating the quality of the feedback and demonstrating the potential of tools like GPT-4 to enhance feedback on code assignments [22]. Vadaparty et al. examined the integration of LLMs in an introductory programming course, focusing on students' experiences and reactions to the LLM's ability to enhance learning and creativity in project-based assessments [23]. Jury et al. developed WorkedGen, a tool that utilizes LLMs to generate interactive worked examples for programming courses. They provided expert evaluations of the generated examples, highlighting the tool's potential to deliver high-quality, scalable educational content and enhance student learning [24]. Lyu et al. conducted a semester-long study on the use of CodeTutor, an LLM-powered assistant, in an entry-level programming course, evaluating students' attitudes over time and showcasing its positive impact on student performance [25]. Among these studies, GenAI was evaluated as a tool to determine whether it can positively impact students' learning. However, to the best of our knowledge, very few studies have focused on how students interact with GenAI tools or provided insights into students' behaviors across different engineering disciplines.

While only a few studies have examined how students interact with GenAI tools, reviewing these works is essential to understanding the needs in this area. Among the limited research available, most of them rely on log data generated by students and GenAI tools, and all studies focus on a single discipline. For instance, Fenu et al. designed a training session in which students interacted with ChatGPT to explore how university students engage with a conversational AI system for programming tasks [26]. The study analyzed students' conversation logs and compared the differences between those who received guidance and those who did not. The study analyzed students' conversation logs and compared the differences between those who received guidance and those who did not. Although studies such as [27, 25] include sections on student interaction with GenAI, their focus is either solely on programming tasks or one aspect of interaction such as categorizations of messages. Therefore, we propose this study to address the gap by providing insights through a comprehensive cross-disciplinary analysis of log data, which identifies categories, patterns, and potential policy violations. By studying students' reactions to and interactions with GenAI tools, we aim to uncover some mechanisms by which these tools benefit student learning.

3 Methodology

Our methodology focuses on analyzing the logged data from AI-bot usage in five engineering courses at a large research university during the Fall 2024 semester. These courses covered various disciplines, including Electrical and Computer Engineering, Computer Science, Civil and

Environmental Engineering, Nuclear, Plasma & Radiological Engineering, and Agricultural and Consumer Economics. The courses ranged from introductory to advanced undergraduate/graduate levels and covered topics such as parallel programming, database systems, structural analysis, nuclear energy systems, and economic analysis in agriculture. During the first few weeks of the semester, instructors announced the availability of an AI-powered AI-bot, emphasizing its purpose as a learning aid rather than a tool for academic dishonesty. Participation was optional and students were encouraged to explore the AI-bot's capabilities, beginning with prompts like "How to succeed in this class," while being reminded to carefully review its outputs and adhere to course policies.

3.1 AI-bot Implementation

The AI-bot was developed as a question-answering model that utilizes multiple Large Language Models, including *llama3.1:70b*, *llama3.1:8b*, *gpt-4o-mini* and *gpt-3.5-turbo*. The system implements a custom Retrieval-Augmented Generation (RAG) framework that consists of four main components: input processing, embedding generation, retrieval, and response generation.

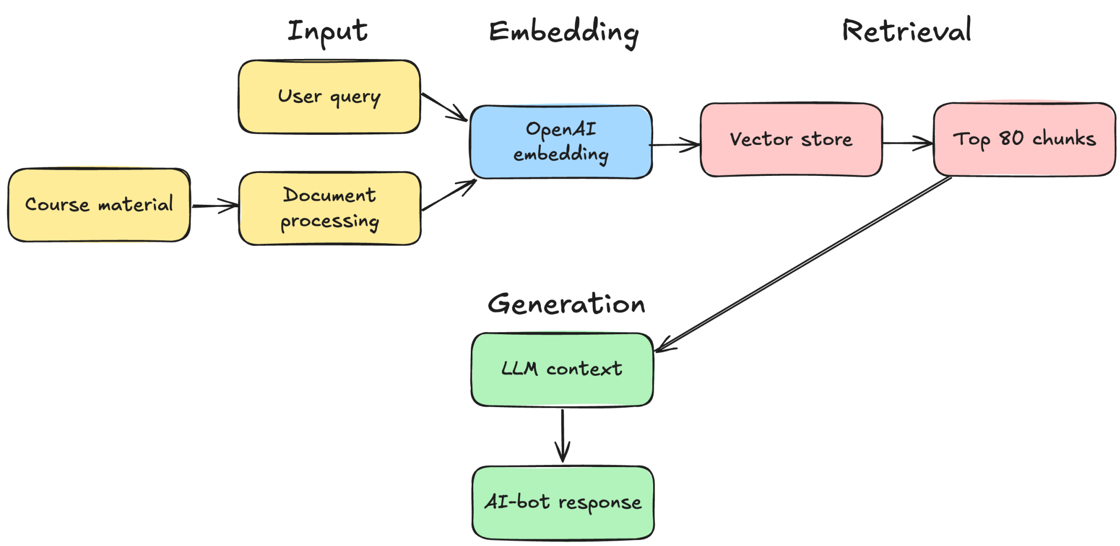

Figure 1: The Architecture of the AI-bot's (RAG) Framework. The system processes inputs (user queries and course materials) through OpenAI embeddings, stores them in a vector store, retrieves relevant chunks, and generates responses using LLM context.

As shown in Figure 1, the system processes course materials, including lecture notes, syllabi, and assignment guidelines, along with user queries during the input stage. These inputs are then transformed into vector representations using OpenAI's embedding model. The embedded course materials are stored in a vector store for efficient retrieval. When a user submits a query, the system compares the query's embedding with the stored course material embeddings to identify the most relevant content. The retrieval component selects the top 80 most relevant document chunks from this comparison. These retrieved chunks are then provided as context to the chosen LLM along with the user's query. The system employs prompt engineering to operate in a question-and-answer mode, enabling the model to generate helpful responses that combine both the retrieved course-specific information and the LLM's pre-trained knowledge.

3.2 Data Collection

Student submissions were logged, anonymized to protect privacy, and processed to eliminate potential biases. We received IRB approval and processed the data with human subject guidelines. The interaction logs were organized into two roles: user messages (student questions) and assistant messages (AI-bot responses). Additionally, course syllabi provided by instructors and the university's student code were collected to evaluate whether student prompts complied with the university's academic integrity policy.

Course	**Users**	**Conversations**	**Level**
Parallel Programming (PP)	501	2926	Advanced
Database Systems (DS)	113	133	Advanced
Engineering Probability and Statistics (EPS)	21	83	Introductory
Nuclear Engineering Fundamentals (NEF)	28	154	Introductory
Careers in Agricultural and Consumer Economics (CACE)	5	17	Introductory

Table 1: Summary of Collected Logs by Course for Fall 2024 semester

As shown in Table 1 the logged data highlights varying levels of engagement across courses, with Parallel Programming showing the highest activity (501 users and 2,926 conversations), while Careers in Agricultural and Consumer Economics had minimal participation (5 users and 17 conversations).

3.3 Data Preparation and Processing

To ensure the consistency and accuracy of our analysis, we implemented a structured approach for data preparation and preprocessing. We used the Pydantic library in Python to create a structured model, *MessageClassification*, which defines key fields such as the message category, confidence score, and explanation. This approach ensured validation and consistency in classifying topics. Additionally, the Instructor package was employed to customize OpenAI API calls, integrating them with a specific system prompt to classify and categorize student messages. The results were returned in a structured *.json* format for further analysis.

```python
class MessageClassification(BaseModel):
    category: MessageCategory
    confidence: float = Field(ge=0, le=1, description="Confidence score for the classification")
    explanation: str = Field(description="Explanation of why the message was classified this way")
```

Figure 2: A Class for classifying student messages, including fields for the message category, a confidence score (ranging from 0 to 1), and an explanation for the classification.

3.3.1 Text Preprocessing

- **Lowercasing:** All text in the message content column was converted to lowercase to eliminate case sensitivity.
- **Tokenization:** Messages were broken down into individual tokens (e.g., words) for detailed linguistic analysis.
- **Lemmatization:** Tokens were reduced to their base forms (e.g., "running" → "run") using SpaCy's NLP pipeline, ensuring normalization of word variations.
- **Stopword removal:** We removed common words like "the" and "is" using the NLTK stopword list so that our analysis could focus on the meaningful terms.

3.3.2 Feature Extraction

- **Part-of-Speech (POS) Tagging:** Each token was tagged with its grammatical role (e.g., noun, verb, adjective) to facilitate linguistic pattern analysis. Moreover, all counts (e.g., POS frequencies, keyword occurrences) were normalized into proportions, allowing for fair comparisons between datasets.

4 Results

In this section, we present our findings for the four research questions. We categorized student queries into five categories and analyzed their distribution across courses (**RQ1**). We also identified patterns in question types and AI-bot usage, highlighting how students engage with the tool differently across various courses (**RQ2**). We further detected the most frequent prompt types, demonstrating how the AI-bot addressed both academic and practical needs across courses (**RQ3**). We lastly identified policy violations to assess compliance challenges (**RQ4**).

4.1 RQ1: Identifying Categories of Student Questions

To address RQ1 *"What categories of questions do students seek help with using the AI-bot?"*, we automated this process by customizing an OpenAI client through the instructor package. This system allowed us to customize a structured output for every user prompt, analyzing each message and assigning it to one of the predefined categories. The example in Figure 3 highlights how the system maps the Message Content as "Conceptual Questions", followed by a confidence score for the classification and includes a brief explanation of why the message was classified into that category. The categories were reviewed and agreed upon by all course instructors to ensure alignment with course objectives and content.

- **Course Logistics**: Questions about schedules, deadlines, or administrative aspects.
- **Programming Help**: Queries related to coding, debugging, or programming concepts.
- **Conceptual Questions**: Questions seeking a deeper understanding of core concepts, with responses typically being explanatory text rather than executable code.
- **Technical Issues**: Problems related to system functionality or technical hurdles.

- **Other**: Messages that did not fit into the above categories.


```
{
   "Message Content": "can we downgrade locks in S2PL",
    "Category": "Conceptual Questions",
    "Confidence": 0.9,
    "Explanation": "The message is asking about the concept of lock downgrading in Strict
      Two-Phase Locking (S2PL), which is a topic related to database concurrency control and
      transaction management."
}
```


Figure 3: A classified JSON object representing a student message classification.

In Figure 4 we highlight the normalized distribution of question categories across five courses. Conceptual Questions consistently dominate the interactions in Parallel Programming (PP), Database Systems (DS), Engineering Probability and Statistics (EPS), and Nuclear Engineering Fundamentals (NEF), representing 62.1%, 67.9%, 51.6%, and 87.5% of prompts, respectively. This suggests that students in these courses rely heavily on the AI-bot for understanding course concepts. In ”Programming Help” it is prominent in PP and DS, accounting for 20.7% and 15.84% respectively, and that reflects the programming-intensive nature of the course.

Among the various categories, ”Course Logistics” shows the highest representation in Careers in Agricultural and Consumer Economics (CACE) at 86.9%, followed by Engineering Probability and Statistics at 31.1%. This might suggest that students in these courses frequently used the AI-bot for clarification about schedules, deadlines, and administrative aspects. In comparison, ”Course Logistics” accounted for less than 10% in other courses. Categories such as ”Technical Issues” were only shown in PP no other course was recorded. ”Other” remains low across all courses except for CACE where it was the second highest among all courses at 21.7%, indicating fewer challenges with system functionality or unclassified queries.

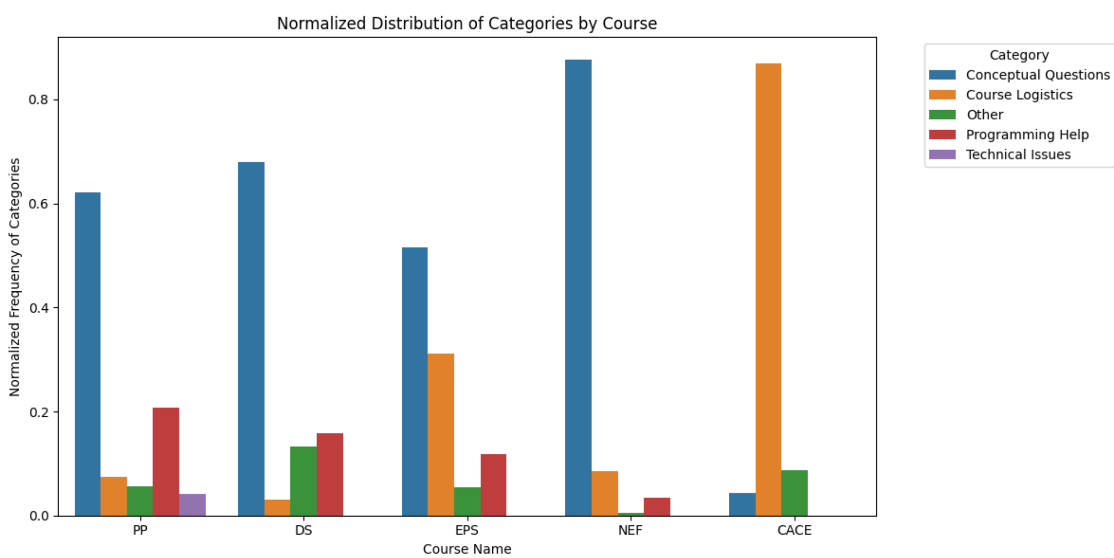

Figure 4: Normalized distribution of question categories across courses. Each bar represents the proportion of questions within a specific category, including ”Conceptual Questions,” ”Course Logistics,” ”Programming Help,” ”Technical Issues,” and ”Other.” The distribution highlights variations in student queries based on course type and content

Table 2 provides illustrative examples of messages classified into each category. The examples demonstrate the variety of student prompts within each category, ranging from specific conceptual inquiries to technical troubleshooting. The trends shown in Figure 4 and the message examples in Table 2 highlight how students engage with the AI-bot based on course content and objectives.

Category	**Message Content**
Conceptual Questions	Give me the formula to calculate probability
Programming Help	Show an example of `<CUDA API>` function usage.
Course Logistics	can you tell me the breakdown of grades in this class?
Technical Issues	i can't seem to connect ssh to delta
Other	What's the weather today

Table 2: Sample Messages Classified into Categories

4.2 RQ2: Examining Patterns of Student Queries

To analyze patterns in student queries across courses, we first tokenized the text, applied lemmatization to normalize word forms (e.g., ”using” $\rightarrow$ ”use”), and removed stopwords such as ”the,” ”is,” ”and,” and ”be” were excluded, as they do not contribute to the semantic content of the queries. The most frequently used tokens for each course were then ranked, as shown in Figure 5. These ranked tokens highlight the distinct focus of each course based on the nature of student queries. For instance, in Parallel programming, tokens such as '=', 'int,' and 'memory' reflect the programming-intensive nature of the course, where students often seek assistance with code and memory management. Similarly, in Database Systems, terms like 'join,' 'lock,' and 'table' emphasize its focus on database management and query optimization. In contrast, Engineering Probability and Statistics queries frequently include 'probability' and 'calculate,' indicating a conceptual and mathematical focus. For Nuclear Engineering Fundamentals, tokens such as 'energy' and 'neutron' highlight its emphasis on technical concepts in nuclear engineering. Finally, Careers in Agricultural and Consumer Economics features general terms like 'assignment' and 'course', suggesting broader discussions related to course assignments and logistics. These results demonstrate how student queries align with the specific requirements and content of each course, reflecting the diverse ways in which students engage with the AI-bot.

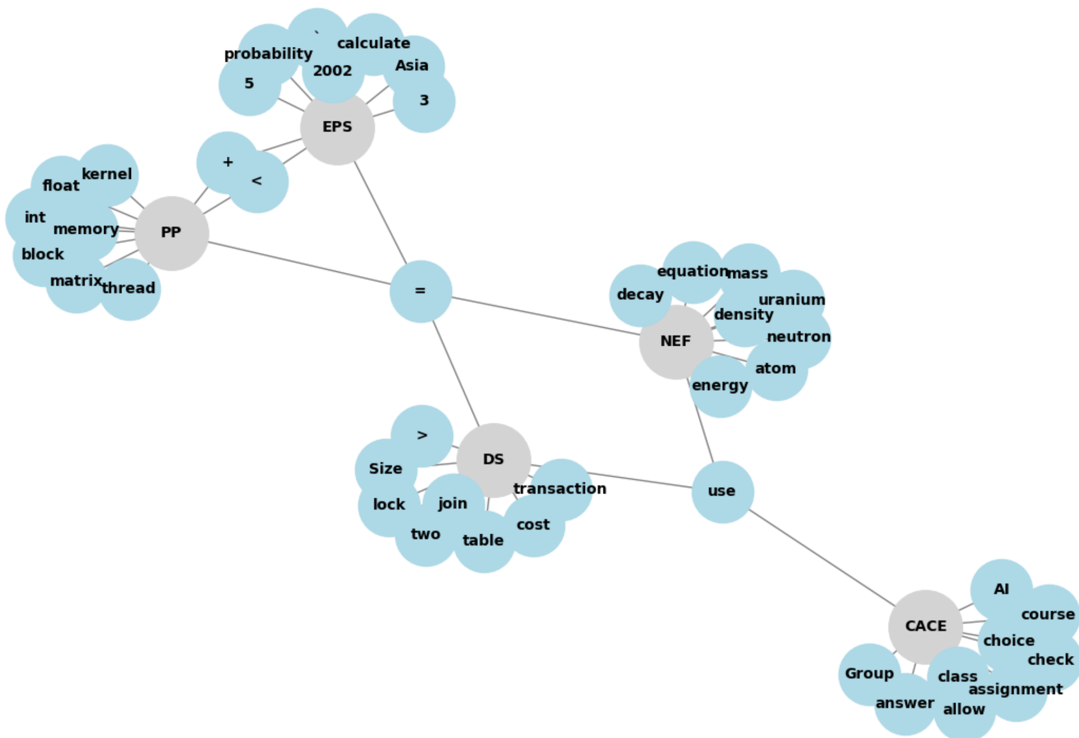

Figure 5: Network graph illustrating the relationships between courses (represented by larger light gray nodes) and their tokens with the highest 10 frequencies (smaller light blue nodes). The graph highlights token distribution across courses and shared tokens.

The analysis revealed distinct patterns in the usage of Part-of-Speech (POS) tags across five primary categories: Conceptual Questions, Course Logistics, Other, Programming Help, and Technical Issues. As shown in Figure 6, ”Nouns” are the most frequently occurring tag across all categories, with the highest normalized count in Technical Issues 42%. This dominance highlights the content-heavy and detail-oriented nature of these queries, which often involve technical concepts or domain-specific terminology. Similarly, ”Proper Nouns” are most prevalent in Programming Help 28.8% and Technical Issues 21.6% which reflects the frequent references to specific programming tools or systems categories. Verbs are the second dominant TAG in categories like Course Logistics 19.7%, Other 18.3%, and Conceptual Questions 16.5%, indicating the action-oriented nature of these questions, such as requests for clarification or instructions. ”Numerals” also play a significant role, particularly in ”Conceptual Questions” 9.47% and ”Other” 11.29%, where numerical data or calculations are often associated with the queries. ”Adposition” and ”Numeral” show distinct patterns across the categories. Adposition is most frequent in ”Course Logistics” at 20.34%, reflecting its role in constructing clarifying or descriptive queries about schedules, assignments, and administrative details. Numeral is most frequent in ”Other” at 11.29% and ”Conceptual Questions” at 9.47%, indicating the inclusion of numerical data in general and conceptual contexts, such as problem-solving or calculations. In contrast, both tags have the lowest counts in ”Programming Help” (Adposition: 8.25%, Numeral:

8.15%) and "Technical Issues" (Adposition: 10.10%, Numeral: 5.47%), reflecting the specialized and detail-oriented nature of these queries, where specific nouns and technical terms dominate. For more insights, Table 3 highlights examples of the words for each POS Tag.

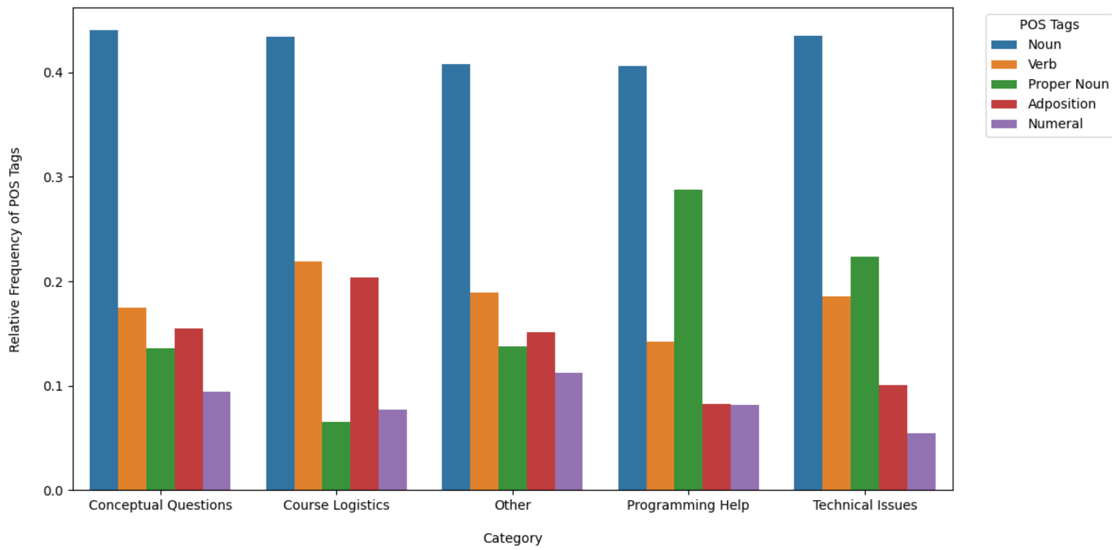

Figure 6: Relative frequency of POS tags across question categories. Nouns dominate all categories. Proper nouns are frequent in 'Programming Help' and 'Technical Issues,' while verbs are prevalent in 'Course Logistics'. Adpositions are common in 'Course Logistics,' and numerals appear most in 'Other'.

POS Tag	**Example Words**
Noun	facts, work, access, languages, assignment
Proper Noun	Google, AI, Format, Americas, Problem
Verb	find, generate, Check, doing, allocate
Adposition	on, of, in, with, to
Numeral	time=64.448, 341, 700

Table 3: Examples of commonly used words are categorized by their Part-of-Speech (POS) tags, selected across multiple categories such as Conceptual Questions, Course Logistics, Programming Help, and Technical Issues.

4.3 RQ3: Analyzing Assignment Types That Drive AI-Bot Usage

Table 4 highlights the most frequently used prompts by students across various courses, categorized by type. Conceptual questions dominate courses like Parallel programming, Database Systems, and Nuclear Engineering Fundamentals. For example, Students asked for clarification on parallel computing operations, database locking mechanisms, and molecular and mass density calculations. This suggests that students primarily use the AI-bot to have a better understanding of complex course material.

On the other hand, prompts related to course logistics, such as accessing course resources (EPS) or clarifying AI usage policies (CACE), demonstrate that while the AI-bot serves as a resource for learning complex concepts, it also addresses practical, logistical needs for students. Due to space limitations, only the top-ranked prompt for each course is included in Table 4.

Course Name	Most Frequent Prompts	Category
Parallel Programming	Considering an exclusive scan operation on an input array of type int, the output vector may differ between a correct CPU implementation and a correct GPU implementation. How about this statement?	Conceptual Questions
Database Systems	Explain the two-phase locking and its takeaway.	Conceptual Questions
Engineering Probability and Statistics	What's the Canvas link?	Course Logistics
Nuclear Engineering Fundamentals	How to find molecular and mass densities.	Conceptual Questions
Careers in Agricultural and Consumer Economics	What am I allowed to use AI for in this class?	Course Logistics

Table 4: A table displaying the most frequently used prompts by students for each course, with a category column for classification.

4.4 RQ4: Exploring Potential Violations of Course Policies

Analysis of AI-bot interactions identified several instances of potential policy violations across courses. To assess these interactions, we referenced the university's student code and course syllabi to cross-check whether the prompts adhered to the policies or not. These interactions primarily fell into the following two categories:

1. **Direct Solution Requests:** Students explicitly asked for answers to assignment questions. For example:

   - *"where can i find the correct answer to past lab quizzes?(PP)*
   - *"give me the correct answer with solution"* (DS)
   - *"what is the code for HW4.5"* (EPS)
   - *solve* $\frac{df(x)}{dx} = -a \cdot f(x) + b$ (NEF)

2. **Assignment Copy-Paste Queries:** Students often pasted entire assignment questions or instructions directly into the AI-bot, seeking solutions. Due to the length and specificity of these queries, as well as their nature, it is not feasible to provide detailed examples here. However, this behavior was observed frequently across multiple courses.

5 Discussion

In our research, we investigated the use of a Generative AI for educational support, our research includes four primary questions. For RQ1, we explored which type of category students usually look for help. In comparison with programming-focused studies such as [27, 25], our research reveals the dominance of conceptual questions, even in programming-focused courses like Parallel Programming and Database Systems. This may be because students have more diverse needs such as clarifying specific concepts or addressing gaps in their knowledge when using such a tool. Moreover, while students often use tools like ChatGPT for general help, the AI-bot system simplifies the process by integrating course materials directly into the AI-bot. This eliminates the need for manual uploads, which makes responses context-aware and customized to the specific course content. This design likely explains why the highest category of queries was conceptual questions, as students relied on the AI-bot to clarify course-specific concepts. Furthermore, the large number of course logistics related queries in CACE suggests the AI-bot's potential to be an administrative aide. Students in Parallel Programming often encounter technical challenges, such as reading from a remote repository or using SSH to access Delta, which likely contributes to the prevalence of this category. Our result reveals differences in query usage across different engineering disciplines.

Our findings addressing RQ2 highlights how course-specific needs influence students' interactions with the AI-bot. In Parallel programming, the frequent tokens show that students commonly need support with programming concepts, debugging, repository management, or understanding CUDA APIs. Similarly, Database Systems queries were about terms like ”join,” ”lock,” and ”table”, which points to students' struggles with database design and optimization. In contrast, Nuclear Engineering Fundamentals' focuses on ”neutron” and ”energy” which suggests a need for guidance on nuclear engineering principles. Each of these three courses has an ”=” in common, which explains that computation and logical reasoning are integral to assignments, which demonstrates the AI-bot's role in helping students overcome computational challenges. In contrast, queries in Careers in Agricultural and Consumer Economics were slightly less technical and more general queries, with tokens like ”class” and ”course” suggesting a dependency on the AI-bot for logistical or administrative support. The significance of tailoring the AI-bot's functionality to the specific demands of each course is highlighted by its patterns, whether it is providing detailed explanations of technical concepts or addressing broader administrative needs.

In all categories, nouns dominated the count. This highlights their central role in student interactions, whether inquiring about assignments or seeking explanations for examples. The high frequency indicates that engaging with the AI-bot often involves using nouns to communicate specific ideas or concepts during back-and-forth exchanges. Proper nouns, on the other hand, were most prevalent in the Programming Help category, suggesting that students frequently referenced specific tools, functions, or systems. In contrast, proper nouns were the least common in Course Logistics, as this category often involves broader, less-specific queries. Interestingly, Course Logistics showed the highest frequency of verbs, highlighting the action-oriented nature of these interactions, such as students finding or asking about assignment deadlines or searching for course-related information.

To address RQ3, the nature of the courses plays a critical role in shaping the types of queries students submit to the AI-bot. Parallel programming and Database Systems, both senior-level undergraduate and breadth graduate courses, are extensive in programming and require technical knowledge. This is why the top-ranked queries for these courses involve conceptual questions, given that students tend to ask for clarification or elaborations of definitions about their assignments. Similarly, in Nuclear Engineering Fundamentals, a second - or third-year course, students primarily ask concept-focused questions, which indicate the need to grasp fundamental principles for technical assignments in nuclear engineering. In contrast, Engineering Probability and Statistics and Careers in Agricultural and Consumer Economics show course logistics as the top category. Although these courses are not necessarily less technical, the prominence of logistics-related prompts may be attributed to limited available data or the possibility that queries in other categories were resolved more efficiently. This suggests that the type of assignments in these courses may require less technical reasoning and more administrative clarity, such as deadlines or course policies.

To explore RQ4, which investigates instances where student's use of the AI-bot violates course policies, it is clear that while there is clarity on what constitutes a violation, there are common patterns of behavior among students, including requests for a solutions or copy-pasting a problem. AI-bot traffic often rises during these high-pressure periods, implying that students can feel pressured while trying to grasp the material within the given time-frame. This urgency might lead them to ask for explicit solutions, as every student takes their time on their learning journey. Additionally, students may consider the AI-bot, being context-aware and can reference course materials, as the only source of solution for verifying their work or seeking answers. A frequent pattern is either students directly asking for solutions, such as programming code or verification of their answers, or copy-pasting entire problems to request solutions. It can be at times challenging to tell between acceptable use and violations in some cases, but there is clear evidence of instances where students explicitly used the AI-bot for help with homework or assessments, violating the boundaries set by course policies.

6 Limitations

This study has several limitations that should be considered when interpreting the findings. The scope of data varied significantly between courses, with some courses having as many as 500 students and others only 35. Also, for intro courses materials are widely available on the internet. For advanced and specialized courses such information is hard to find making a course-specific bot more useful. This discrepancy may have influenced the frequency and variety of AI-bot interactions analyzed. Additionally, the findings are based on data from five courses, which limits the ability to generalize the results to other disciplines or to courses with differing levels of complexity and concepts. Furthermore, the study did not incorporate direct feedback from students about their perceptions of the AI-bot or its impact on their learning. Addressing these limitations in future studies would enhance the breadth and depth of the analysis.

7 Conclusions and Future Work

In this study, we explored the use of a Generative AI-powered AI-bot in educational settings by addressing four research questions. We examined the categories of questions students seek help with, revealing that conceptual questions dominate in courses like Parallel programming, Database Systems, and Nuclear Engineering Fundamentals. We also analyzed patterns in question types across courses by analyzing the most frequently used words in each course and identifying POS (Part-of-Speech) tags for each category. The results revealed a range of patterns, from problem-solving queries in programming-heavy courses to logistical questions in less technical courses. We further identified the types of assignments that prompt AI-bot use, revealing that assignments, such as those in Parallel programming and Database Systems, requiring deeper conceptual understanding lead to substantial engagement with the AI-bot In contrast, courses like Engineering Probability and Statistics as well as Careers in Agricultural and Consumer Economics emphasized logistical queries, reflecting the varied needs of students across topics and the adaptability of the GenAI tool. Finally, we explored potential policy violations, uncovering instances of direct solution requests and assignment copy-pasting during high-pressure periods such as deadlines and exams. These findings reveal patterns in how students interact with GenAI tools and underscore their nuanced role in education, highlighting their potential to support diverse student needs.

Future work could expand this study by analyzing data from a broader range of courses to better understand how students across different disciplines interact with AI-bots. As computer vision technologies advance, future models could also be designed to assist with courses that involve drawing or design-based assignments. Incorporating student feedback through surveys or interviews would provide more in-depth insights into how AI-bots influence learning experiences and areas for improvement. It would be valuable to include the students' and faculty members' perspectives on how AI was used, as this would clarify their motivations, and overall satisfaction. Furthermore, developing automated systems to detect and address policy violations in real-time could promote more ethical and effective use of the AI-bot.

References

[1] S. Feuerriegel, J. Hartmann, C. Janiesch, and P. Zschech, "Generative AI," *Business & Information Systems Engineering*, vol. 66, no. 1, pp. 111–126, 2024.

[2] A. Yusuf, N. Pervin, M. Román-González, and N. M. Noor, "Generative AI in Education and Research: A Systematic Mapping Review," *Review of Education*, vol. 12, no. 2, p. e3489, 2024.

[3] U. Mittal, S. Sai, V. Chamola *et al.*, "A Comprehensive Review on Generative AI for Education," *IEEE Access*, 2024.

[4] R. Liu, C. Zenke, C. Liu, A. Holmes, P. Thornton, and D. J. Malan, "Teaching CS50 with AI: Leveraging Generative Artificial Intelligence in Computer Science Education," in *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, ser. SIGCSE 2024. New York, NY, USA: Association for Computing Machinery, 2024, pp. 750–756. [Online]. Available: https://doi.org/10.1145/3626252.3630938

[5] A. S. Fernandez and K. A. Cornell, “CS1 with a Side of AI: Teaching Software Verification for Secure Code in the Era of Generative AI,” in *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, ser. SIGCSE 2024. New York, NY, USA: Association for Computing Machinery, 2024, pp. 345–351. [Online]. Available: https://doi.org/10.1145/3626252.3630817

[6] P. Prasad and A. Sane, “A Self-Regulated Learning Framework Using Generative AI and Its Application in CS Educational Intervention Design,” in *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, ser. SIGCSE 2024. New York, NY, USA: Association for Computing Machinery, 2024, pp. 1070–1076. [Online]. Available: https://doi.org/10.1145/3626252.3630828

[7] E. A. Alasadi and C. R. Baiz, “Generative AI in Education and Research: Opportunities, Concerns, and Solutions,” *Journal of Chemical Education*, vol. 100, no. 8, pp. 2965–2971, 2023.

[8] H. Nguyen and V. Allan, “Using GPT-4 to Provide Tiered, Formative Code Feedback,” in *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, ser. SIGCSE 2024. New York, NY, USA: Association for Computing Machinery, 2024, pp. 958–964. [Online]. Available: https://doi.org/10.1145/3626252.3630960

[9] P. Denny, J. Leinonen, J. Prather, A. Luxton-Reilly, T. Amarouche, B. A. Becker, and B. N. Reeves, “Prompt Problems: A New Programming Exercise for the Generative AI Era,” in *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, ser. SIGCSE 2024. New York, NY, USA: Association for Computing Machinery, 2024, pp. 296–302. [Online]. Available: https://doi.org/10.1145/3626252.3630909

[10] S. Lau and P. Guo, “From Ban It Till We Understand It ̈to Ë̈Resistance is Futile ̈: How University Programming Instructors Plan to Adapt as More Students Use AI Code Generation and Explanation Tools Such as ChatGPT and GitHub Copilot,” in *Proceedings of the 2023 ACM Conference on International Computing Education Research - Volume 1*, ser. ICER ’23. New York, NY, USA: Association for Computing Machinery, 2023, pp. 106–121. [Online]. Available: https://doi.org/10.1145/3568813.3600138

[11] Ö. M. Akkaş, C. Tosun, and Ş. Gökçearslan, “Artificial Intelligence (AI) and Cheating: The Concept of Generative Artificial Intelligence (GenAI),” in *Transforming Education With Generative AI: Prompt Engineering and Synthetic Content Creation*. IGI Global, 2024, pp. 182–199.

[12] B. Chen, C. M. Lewis, M. West, and C. Zilles, “Plagiarism in the Age of Generative AI: Cheating Method Change and Learning Loss in an Intro to CS Course,” in *Proceedings of the Eleventh ACM Conference on Learning @ Scale*, ser. L@S ’24. New York, NY, USA: Association for Computing Machinery, 2024, pp. 75–85. [Online]. Available: https://doi.org/10.1145/3657604.3662046

[13] S. Gökoğlu and F. Erdoğdu, “The Effects of GenAI on Learning Performance: A Meta-Analysis Study.”

[14] F. E. Oguz, M. N. Ekersular, K. M. Sunnetci, and A. Alkan, “Can ChatGPT Be Utilized in Scientific and Undergraduate Studies?” *Annals of Biomedical Engineering*, vol. 52, no. 5, pp. 1128–1130, 2024.

[15] E. Kasneci, K. Seßler, S. Küchemann, M. Bannert, D. Dementieva, F. Fischer, U. Gasser, G. Groh, S. Günnemann, E. Hüllermeier *et al.*, “ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education,” *Learning and Individual Differences*, vol. 103, p. 102274, 2023.

[16] M. Abedi, I. Alshybani, M. R. B. Shahadat, and M. Murillo, “Beyond Traditional Teaching: The Potential of Large Language Models and Chatbots in Graduate Engineering Education,” *Qeios*, 2023.

[17] D. Baidoo-Anu and L. O. Ansah, “Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning,” *Journal of AI*, vol. 7, no. 1, pp. 52–62, 2023.

[18] F. Osasona, O. O. Amoo, A. Atadoga, T. O. Abrahams, O. A. Farayola, and B. S. Ayinla, “Reviewing the Ethical Implications of AI in Decision Making Processes,” *International Journal of Management & Entrepreneurship Research*, vol. 6, no. 2, pp. 322–335, 2024.

[19] K. Wach, C. D. Duong, J. Ejdys, R. Kazlauskaitė, P. Korzynski, G. Mazurek, J. Paliszkiewicz, and E. Ziemba, "The Dark Side of Generative Artificial Intelligence: A Critical Analysis of Controversies and Risks of ChatGPT," *Entrepreneurial Business and Economics Review*, vol. 11, no. 2, pp. 7–30, 2023.

[20] P. Haindl and G. Weinberger, "Students' Experiences of Using ChatGPT in an Undergraduate Programming Course," *IEEE Access*, vol. 12, pp. 43 519–43 529, 2024.

[21] C. K. Tiwari, M. A. Bhat, S. T. Khan, R. Subramaniam, and M. A. I. Khan, "What Drives Students Toward ChatGPT? An Investigation of the Factors Influencing Adoption and Usage of ChatGPT," *Interactive Technology and Smart Education*, vol. 21, no. 3, pp. 333–355, 2024.

[22] H. Gabbay and A. Cohen, "Combining LLM-Generated and Test-Based Feedback in a MOOC for Programming," in *Proceedings of the Eleventh ACM Conference on Learning @ Scale*, ser. L@S '24. New York, NY, USA: Association for Computing Machinery, 2024, pp. 177–187. [Online]. Available: https://doi.org/10.1145/3657604.3662040

[23] A. Vadaparty, D. Zingaro, D. H. Smith IV, M. Padala, C. Alvarado, J. Gorson Benario, and L. Porter, "CS1-LLM: Integrating LLMs into CS1 Instruction," in *Proceedings of the 2024 on Innovation and Technology in Computer Science Education V. 1*, ser. ITiCSE 2024. New York, NY, USA: Association for Computing Machinery, 2024, pp. 297–303. [Online]. Available: https://doi.org/10.1145/3649217.3653584

[24] B. Jury, A. Lorusso, J. Leinonen, P. Denny, and A. Luxton-Reilly, "Evaluating LLM-Generated Worked Examples in an Introductory Programming Course," in *Proceedings of the 26th Australasian Computing Education Conference*, ser. ACE '24. New York, NY, USA: Association for Computing Machinery, 2024, pp. 77–86. [Online]. Available: https://doi.org/10.1145/3636243.3636252

[25] W. Lyu, Y. Wang, T. R. Chung, Y. Sun, and Y. Zhang, "Evaluating the Effectiveness of LLMs in Introductory Computer Science Education: A Semester-Long Field Study," in *Proceedings of the Eleventh ACM Conference on Learning @ Scale*, ser. L@S '24. New York, NY, USA: Association for Computing Machinery, 2024, pp. 63–74. [Online]. Available: https://doi.org/10.1145/3657604.3662036

[26] G. Fenu, R. Galici, M. Marras, and D. Reforgiato, "Exploring Student Interactions with AI in Programming Training," in *Adjunct Proceedings of the 32nd ACM Conference on User Modeling, Adaptation and Personalization*, ser. UMAP Adjunct '24. New York, NY, USA: Association for Computing Machinery, 2024, pp. 555–560. [Online]. Available: https://doi.org/10.1145/3631700.3665227

[27] B. Ma, L. Chen, and S. Konomi, "Enhancing Programming Education with ChatGPT: A Case Study on Student Perceptions and Interactions in a Python Course," in *International Conference on Artificial Intelligence in Education*. Springer, 2024, pp. 113–126.