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Key Features of GPT Learning Paradigm

Mădălina Pană*

A R T I C L E I N F O

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A B S T R A C T

The continuous advancement of technology has always sparked debates, much like earlier shifts in history. From the introduction of computers in the mid-20th century to the rise of the internet in the 2000s, each innovation has brought both excitement and apprehension. Today, a new era is emerging, where technology becomes deeply embedded in daily life. While innovations like AI in medical imaging, such as using it for tumor detection in radiographs, are widely accepted, other technologies, such as virtual reality, still face skepticism due to fear of the unfamiliar and resistance to change. However, stopping technological advancement is not the answer. The focus should instead be on guiding and managing AI development, particularly in education. This new learning model highlights the integration of AI into educational systems, especially for students pursuing programming. Through responsible implementation, AI can improve the learning experience while minimizing the potential downsides of unchecked technological growth. This study explores how AI can reshape education and provides practical ways to ensure its controlled and effective adoption in academic settings. Beyond this, AI has the potential to enhance how students engage with challenging topics, promoting creativity and innovation. For programming students, AI tools can optimize coding practices, detect mistakes, and suggest improvements. Additionally, AI-powered platforms encourage collaborative learning across borders, enriching education and preparing students for a globally connected workforce. By embracing AI and using it ethically, educational systems can create a more inclusive and forward-thinking environment.

1. Introduction

In the realm of education, technological progress, particularly in the realm of artificial intelligence, is met with divergent perspectives. Some nations have prohibited the use of GPT in educational and corporate settings, while others lack stringent controls over AI utilization. Education, by its definition, entails the accumulation of competencies within a given domain. Traditionally, competencies encompass declarative knowledge (theoretical information acquisition), procedural knowledge (acquisition of practical skills within the chosen domain), and values (learning to appreciate and apply the principles of the chosen domain).

Presently, educational paradigms have shifted from those prevalent until the early 20th century. Previously, individuals primarily acquired theoretical knowledge (declarative competencies) without mastering the abstraction of concepts or the ability to draw analogies between hypotheses. However, contemporary education emphasizes procedural knowledge over theoretical knowledge. Because of this, psychologists have raised concerns regarding the decline in the intelligence quotient across generations, particularly in the period from the advent of the internet to the present day.

In contemporary education, the integration of technology has spurred the evolution of e-learning, offering unprecedented accessibility and flexibility to learners worldwide. Despite its advantages, personalized student assistance remains a formidable challenge in digital learning environments. This article explores the potential of unsupervised artificial intelligence (AI) models, specifically GPT and Gemini, in addressing this challenge by providing tailored explanations and hints to students navigating e-learning platforms.

During the past decade, the interest in different Computer Assisted Learning Systems (CALs) has been increased (Mtebe et al., 2014). E-learning platforms have become ubiquitous, catering to diverse learning styles and preferences. However, the efficacy of student support mechanisms often falls short of meeting individual needs, leading to suboptimal learning experiences. Unsupervised AI presents a promising avenue for enhancing student assistance by leveraging unstructured data to deliver personalized guidance.

In today's educational systems, evaluating students' knowledge and skills is an integral part of the learning process. Traditional evaluation methods often involve manual grading, which can be time-consuming,

* Bucharest University of Economic Studies, Bucharest, Romania. E-mail address: madalina.pana@csie.ase.ro (M. Pana)

subjective, and resource intensive. By incorporating GPT, an advanced AI model, into student evaluation, professors can unlock new possibilities for enhancing the educational experience(Russo et al., 2022).

One of the GPT's capability is to process and analyse vast amounts of information, enabling professors to efficiently evaluate students' work. Through automated grading, professors can save significant time, allowing them to focus on providing individualized instruction and feedback (Saxe et al., 2021). Moreover, GPT can help maintain consistency in grading standards, reducing human bias in evaluations.

GPT's language generation abilities empower professors to deliver personalized feedback for each student. The model can identify areas of improvement, provide tailored suggestions, and offer specific examples to enhance learning outcomes. Students receive immediate and detailed feedback, promoting a deeper understanding of their strengths and weaknesses, thus enabling them to take ownership of their learning journey.

The implementation of GPT in student evaluation can foster critical thinking skills by challenging students to think analytically and creatively. The model's ability to generate questions and prompts can encourage students to explore complex ideas, formulate thoughtful responses, and develop higher-order thinking skills. By engaging with GPT, students are exposed to a wider range of perspectives and ideas, enriching their learning experience. On the other hand, GPT can assist in creating inclusive learning environments by accommodating diverse learning needs. The model can adapt to individual students' learning styles, offering customized resources, adaptive assessments, and alternative explanations. This inclusivity can empower students with different abilities, backgrounds, and learning preferences to thrive in their educational journey.

While GPT offers numerous advantages, its implementation in schools must address certain challenges. Issues such as data privacy, ethics, and the potential for overreliance on AI need careful consideration. Educators must strike a balance between leveraging AI for evaluation and maintaining the human connection necessary for effective teaching and learning.

In the content of this article, detailed information about the architecture of the GPT, what it takes to use such system, the results of our scenario can be found, having the following structure:

- ✧ Chapter II. Literature review: this section is presenting general characteristics of GPT as architecture and structure, techniques and best practices for sending prompts, similar approaches from other studies including analysing advantages and vision.
- ✧ Chapter III. Methodology: this section outlines the approach taken to evaluate the efficacy of unsupervised AI in e-learning
- ✧ Chapter III. Proposed model: it contains the whole structure of the scenario execution, with the explanation for each step.
- ✧ Chapter IV. Results and discussion: it includes the results from the testing process.
- ✧ Chapter V. Conclusions and future work: it contains a summary of this article, including advantages and possible research paths.

2. Literature review

In the realm of education, the integration of technology has revolutionized traditional learning methods, giving rise to the phenomenon of e-learning. E-learning platforms offer flexibility and accessibility, catering to diverse learners worldwide. However, ensuring personalized and effective support for students remains a significant challenge in this digital landscape. This article explores the potential of unsupervised artificial intelligence (AI) in addressing this challenge, particularly focusing on the utilization of models such as GPT and Gemini to provide tailored explanations and hints to students navigating e-learning environments.

The GPT is built upon with a deep neural network architecture known as GPT (Generative Pre-trained Transformer). The basic structure of GPT is a transformer model, which is a sort of neural network specifically built to handle sequential input, like as text (Devlin et al., 2019). The GPT model is made up of numerous layers of attention mechanisms and feed-forward neural networks (Cichy et al., 2019). During the training phase, it learns to estimate the likelihood of the next word in a phrase based on the preceding words in the sequence (Schrimpf et al., 2021). This method allows the model to capture the correlations and patterns contained in the training data, allowing it to provide coherent and contextually relevant replies (Atanasova et al., 2020).

GPT develops its comprehension and ability to produce text across a range of themes and writing styles by training on a variety of text data. It is not capable of carrying out activities in the actual world or having access to real-time information (Richards et al., 2019). It only uses the knowledge it has learned through training, as opposed to other sources.

Multiple layers of self-attention mechanisms and feed-forward neural networks comprise the model (Heilbron et al., 2022). Here is a more in-depth explanation of how it works:

- ✧ Tokenization: Before displaying a text prompt or inquiry, it is tokenized into smaller pieces known as tokens. Tokens are individual words or sub-words that help represent input text in a fashion that the model understands.
- ✧ Encoding: The tokenized input is then processed by the model's encoder. To do so, the tokens must pass through multiple layers of self-attention mechanisms and feed-forward networks. The self-attention

mechanism enables the model to evaluate the significance of various tokens in the context of the complete input sequence.

- ✧ Context understanding: As the input text is decoded, the model creates an internal representation of the text that captures its context and meaning. It examines the links between words, phrases, and other textual elements to determine the semantics of the input.
- ✧ Response generation: After decoding and comprehending the input, the model creates a response by anticipating the tokens that will likely come next based on the context it has learnt. It generates a string of tokens that together make up the response text.
- ✧ Decoding: The created token sequence is then translated into text that can be read by humans. To construct the final response, the tokens must be changed into words or phrases.

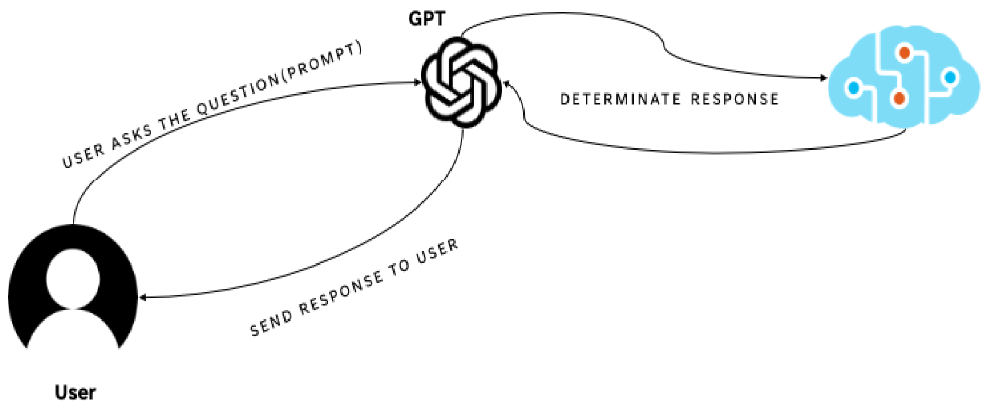

Figure 1. GPT-User interaction
Source: Author's representation

Previous research has extensively examined the role of AI in enhancing educational experiences, with a particular emphasis on supervised learning approaches. While these methods have shown promise in various applications, they often rely on labelled data and predefined rules, limiting their adaptability to diverse learning contexts. In contrast, unsupervised AI models like GPT and Gemini offer the advantage of learning patterns and generating insights from unstructured data without explicit supervision. Studies have indicated the potential of such models in improving student engagement and learning outcomes by providing personalized assistance and feedback

Existing literature extensively examines the role of AI in education, with supervised learning approaches dominating the discourse. While effective in certain contexts, these methods rely heavily on labelled data and predefined rules, limiting their adaptability to dynamic learning environments. In contrast, unsupervised AI models offer the advantage of learning from unstructured data without explicit guidance, thus enabling more flexible and adaptive solutions.

Studies have shown the potential of unsupervised AI in various educational applications, including content recommendation, student feedback generation, and personalized tutoring. Models such as GPT and Gemini, trained on vast amounts of textual data, demonstrate remarkable proficiency in understanding and generating human-like responses. By analysing student interactions within e-learning platforms, these models can infer underlying patterns and provide tailored explanations and hints to facilitate learning.

In the worldwide, there are several studies and surveys that provide insight into how prevalent this GPT usage has become:

- ✧ Usage Among High School Students: A survey by the Pew Research Center found that about 25% of 11th and 12th graders who are aware of ChatGPT have used it for schoolwork. This percentage drops to 17% among 9th and 10th graders and 12% among 7th and 8th graders.
- ✧ College Student Usage: Nearly one-third of college students used ChatGPT for schoolwork during the 2022-2023 academic year, according to a survey by Intelligent.com. Another survey from BestColleges indicated that about half of the college students consider using AI tools like ChatGPT as cheating, yet 20% still use them (Ohio Capital Journal). The adoption rate among college students rose from 27% in spring 2023 to 49% in fall 2023. Daily users often use AI for summarizing text, organizing schedules, and answering homework questions, while less frequent users employ it to understand difficult concepts and assist with writing assignments (Source: TAC 2023).
- ✧ Faculty Perspectives and Usage: Faculty usage of AI writing tools increased from 9% in spring 2023 to 22% in fall 2023. Many faculty members use AI to understand what students might be seeing and to teach students effective use of these tools. About 43% of faculty use AI to create more engaging in-class activities (Inside Higher Ed). While there is some concern about AI's impact on learning, a growing number of faculty believe students need to learn to use AI to succeed in the workforce. In the spring of

2023, 50% of faculty thought AI would negatively impact learning, but this decreased to 39% by fall 2023 (Source: TAC 2023).

In terms of adoption, the educational sector is still grappling with the implications of AI tools like ChatGPT. Some institutions have initially banned such tools due to concerns about academic integrity, only to later lift these bans to explore more constructive ways of integrating AI into the curriculum. For example, Italy temporarily banned ChatGPT in March 2023 due to privacy concerns, specifically issues related to the processing of users' personal data. The ban was lifted after OpenAI complied with local regulations.

Another example is Russia, they restricted access to ChatGPT in response to the geopolitical situation, specifically the Russia-Ukraine war. There are also other countries such as: Iran, North Korea, Syria, Cuba, and Hong Kong, that have also restricted or blocked access to ChatGPT due to various reasons, including heavy censorship and strict internet regulations.

Not only Educational Institutions have blocked AI tools, but also Corporations, here there are included companies in sectors like banking, healthcare, and technology. For instance, JPMorgan Chase, Apple, and Verizon have limited or banned its use over concerns about data security and confidentiality. These measures reflect a cautious approach towards integrating AI tools like ChatGPT in sensitive areas, emphasizing the need for robust governance and regulatory frameworks to address potential risks while harnessing the benefits of AI technology.

3. Methodology

Schools have increasingly adopted online platforms that incorporate various learning resource tools. As a result, the eLearning approach has become more intricate compared to traditional methods as it offers greater flexibility in terms of time and space. However, it's important to note that the traditional method and eLearning are not mutually exclusive; in fact, both approaches can yield positive and improved outcomes.

The integration of AI in education is fostering a new paradigm of learning that emphasizes personalization, accessibility, and enhanced engagement. Here are some keyways AI is transforming education:

- ✧ Personalized Learning: AI-driven platforms analyse individual student data to tailor educational content, providing personalized learning pathways. This approach helps address diverse learning needs and paces, enhancing student engagement and effectiveness.
- ✧ Enhanced Learning Resources: AI tools like chatbots and virtual tutors offer immediate assistance, helping students understand complex topics outside of traditional classroom hours. These resources provide explanations, answer questions, and offer feedback on assignments.
- ✧ Data-Driven Insights: AI helps educators by analysing large datasets to identify trends and areas where students struggle. This allows for data-driven decision-making in curriculum design and teaching strategies, aiming to improve overall educational outcomes.
- ✧ Automated Administrative Tasks: AI automates routine administrative tasks such as grading and scheduling, freeing up educators to focus more on teaching and student interaction. This can increase efficiency and reduce the administrative burden on teachers.
- ✧ Collaborative Learning: AI facilitates collaborative learning through platforms that enable group projects and discussions, irrespective of geographical barriers. This fosters a global learning environment and enhances communication skills among students.
- ✧ Ethical and Practical Considerations: While AI offers significant benefits, it also raises concerns about data privacy, the potential for reduced human interaction, and the ethical use of AI-generated content. Establishing guidelines and ethical standards is crucial to address these challenges (Nature).

Overall, the AI revolution in education is creating more dynamic, personalized, and efficient learning experiences, but it also requires careful consideration of ethical and practical implications to ensure positive outcomes for all stakeholders.

This section outlines the approach taken to evaluate the efficacy of unsupervised AI in e-learning. To test our scenario, we first started with an easy math test, to see if ChatGPT is capable to evaluate it. As it can be seen in the following picture (Figure 2), GPT response was short and on point, and it contains the following:

- ✧ Feedback: for each question, it is analyzing the response and gives feedback if its correct or not, explaining how many points it is giving.
- ✧ Feelings: after making the total of points, GPT is ending the response with a congratulation note, expressing positive feelings.
- ✧ Model training: even though GPT did not know from its pre-trained dataset how should evaluate the responses, it started training and learning how many points each question has and what is the maximum points.

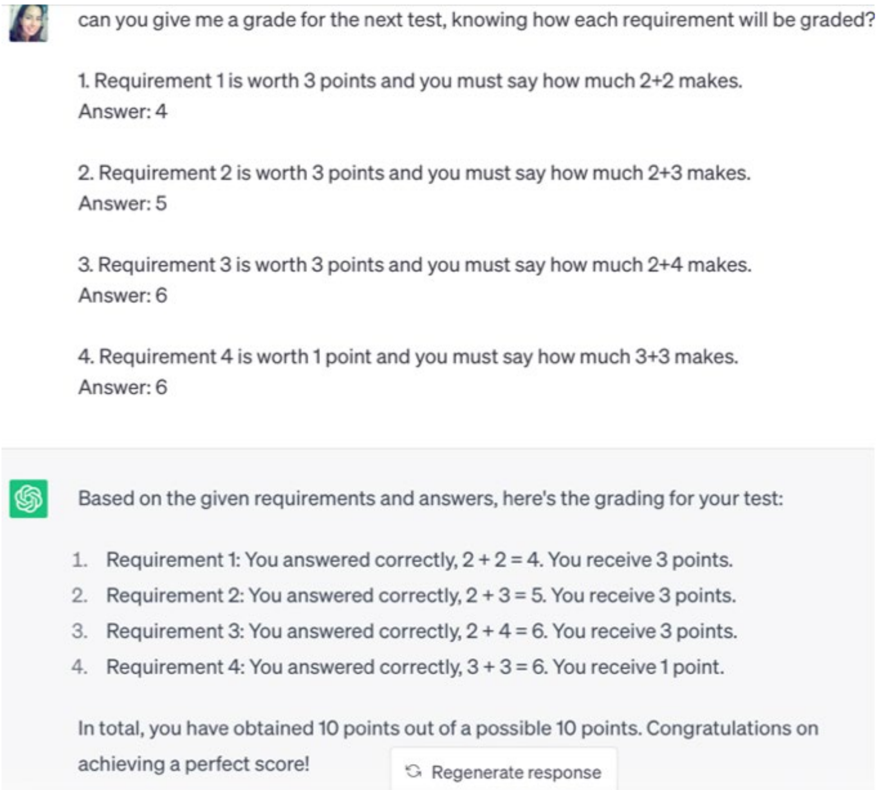

Figure 2. GPT response

Source: chat.openai.com

When using GPT, an important aspect, that it might be at some point challenging, is the way that you "build" the question. The same situation might also happen when we use Google search, even though GPT and Google search utilize different algorithms and serve different purposes.

Google's search algorithm is highly sophisticated and involves various components like crawling, indexing, and ranking (Rousseau, 2010). It continuously updates its index to provide users with the most relevant and up-to-date search results based on their queries.

The algorithm considers factors like relevance, popularity, user location, and various other signals to deliver the most useful results. However, the key for this algorithm stays in what the user types in the search-bar. For example, during one of the laboratories, the students were asked how to make the background yellow for a paragraph using only html and because this was the first programming course, they were asked how they would search on Google to get the solution of their problem.

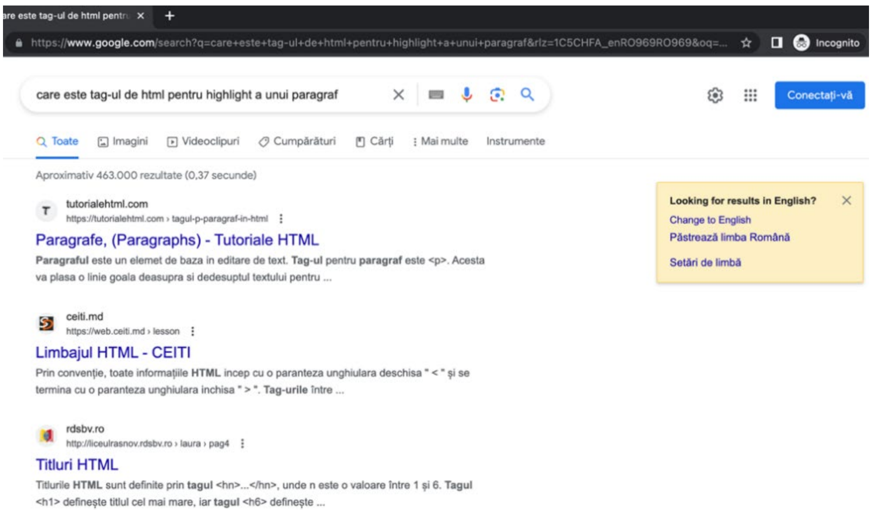

Figure 3. First attempt to search the answer

Source: online laboratory

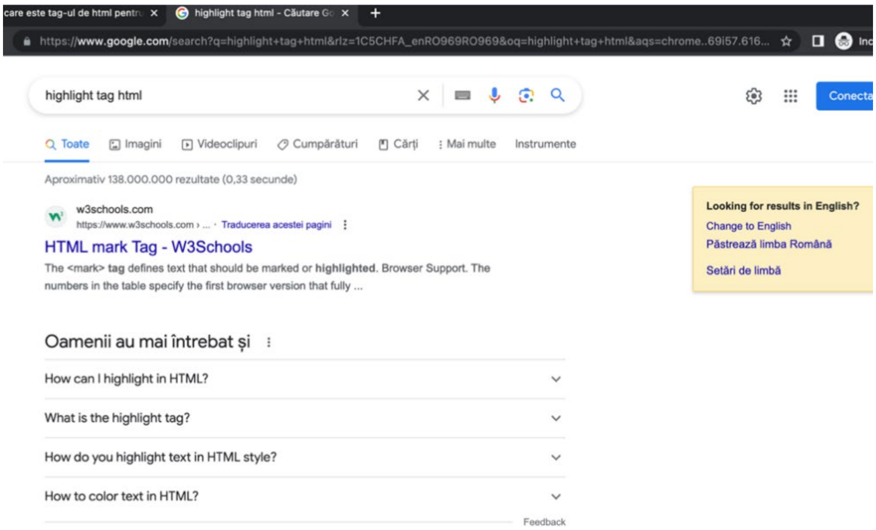

Figure 4. Second attempt to search the answer

Source: online laboratory

The first picture (Figure 3.) represents students' version of how to search for "What is the HTML tag for highlighting a paragraph", in Romanian language - which can make mapping between those words and solution to be challenging. The first three results in this example are not satisfying, so students tried a second time with "highlight tag html" which made the first result to be the desired one (Figure 4.). This is a usual example where it is necessary to summarize the question by eliminating the words that do not have a certain scope in the phrase.

The same situation happens with the text that the user sends to GPT, which is called "prompt". There are several studies that present how user should write a prompt correctly and even OpenAI launched a course for "Prompt Engineering" (OpenAI and DeepLearningAI, 2023).

Large language models (LMs) can be prompted to perform a range of natural language processing (NLP) tasks, given some examples of the task as input. However, these models often express unintended behaviours such as making up facts, generating biased or toxic text, or simply not following user instructions (Si et al., 2022).

One possible solution for this prompting issue is summarizing questions (Wu et al., n.d.), where task breakdown and learning from user feedback are combined in this process.

The process begins with receiving a text prompt, which represents the question or request for the neural network. The prompt is then divided into smaller units called tokens, which may be words or characters, through a process known as tokenization. These tokens are analyzed by the neural network, which employs layers and mathematical models to understand their relationships and structure. After tokenization and processing, the neural network generates a response based on this analysis, structuring the output according to the extracted information. Finally, the generated response is delivered as the output, providing the solution or information requested in the initial prompt (Christiano et al., 2017).

4. Proposed model

Training models to carry out activities that are too complicated or time-consuming for humans to determine is a significant challenge for scaling machine learning. There are significant difficulties with teaching and assessing programming abilities in school contexts, especially when using the C++ language.

We started to test our scenario by giving the context to GPT: "You are a University Computer Science teacher that needs to grade some Object-Oriented Programming in C++ tests". Then, we created two sections, one for requirements and another one with the test that needs to be evaluated.

This is an example of a requirement using prompt:

"Here are the requirements including the given points:
** The solution does not contain compilation errors - 1 point*
** Requirement A (testA) - 0.5 points*
Add the following private attributes to the BankAccount class:
(the name must match the one specified below)
owner - string representing the owner of the bank account
nr_transactions - integer representing the number of transactions
transactions - vector dynamically allocated by float representing
the actual transactions"

After all requirements were set, we added the code for every student: "Here is the student's test that you need to give a grade based on the requirements already provided".

We compile a sizable dataset of C++ annotation-based programming tests to train the GPT model for programming evaluation. The dataset consists of a wide variety of programming exercises that cover a range of ideas and levels of difficulty. Each exam entry is manually graded by knowledgeable teachers, offering an accurate basis for comparison.

On the gathered programming test dataset, we apply the pre-trained GPT model and adjust it. By lining up the generating output of the GPT with the expert-annotated grades, we highlight the value of precise grading during fine-tuning. With the help of this procedure, the model is better able to produce pertinent and accurate grades for student contributions.

In Figure 5 it can be seen the power of prompting combined with meta-learning, where any user can make GPT a specialist for various jobs without modifying the original model. Although the baseline GPT does not know how to accomplish any activity, it does know how to learn how to do so, making it more powerful and adaptable.

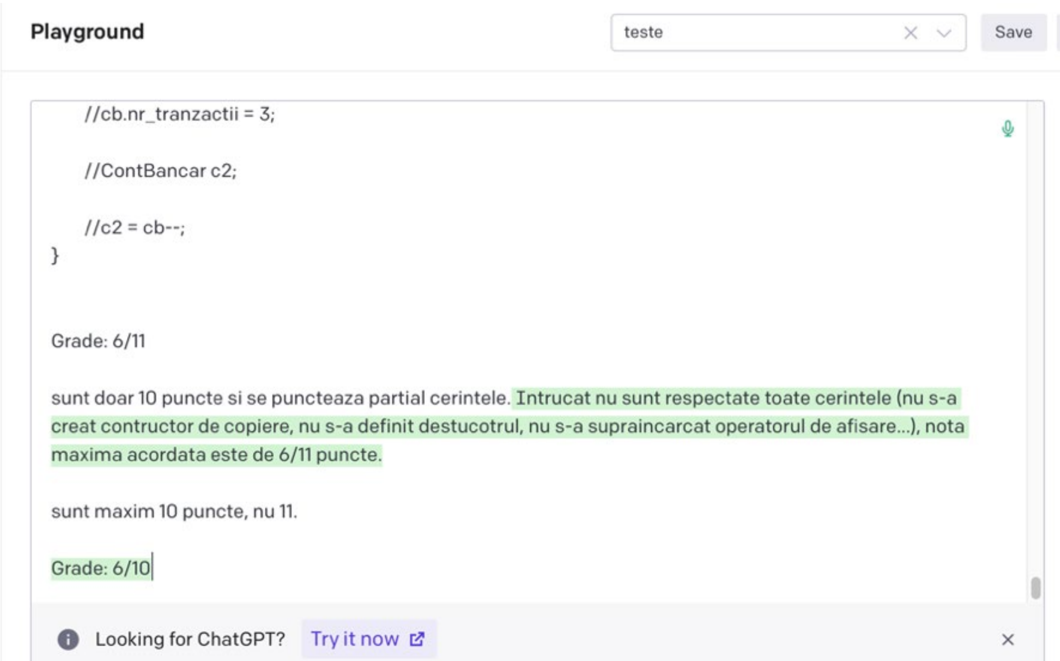

Figure 5.GPT training

Source: openai.com

5. Results

After sending all the students' tests to GPT, we analysed the responses to decide if AI can be used to automate this evaluation process. A part of the responses can be seen in the following table:

Nr.crt.	Student	Grade (Professor)	Grade (GPT)
1	Student A	3	2
2	Student B	7	5
3	Student C	4	4
4	Student D	9	6
5	Student E	5	4
6	Student F	3	4
7	Student G	6	5
8	Student H	3	4
9	Student I	8	5
10	Student J	7	5
	Average	5.5	4.4
	Root Mean Square Error	1.760681686	
	Correlation Coefficient	0.836711677	

To assess the performance of the GPT-based evaluation system, we evaluated the feedback generated by GPT for its relevance, coherence, and effectiveness.

The correlation coefficient obtained was 0.83. This can be interpreted as a high degree of correlation between the scores offered by the teachers and the ones computed by the model. The root mean square error was also calculated to determine if there are major deviations from the mean between the scores provided by the teachers and the model.

The root means square error obtained was 1.76. This can be interpreted as an acceptable deviation from the mean between the two teachers.

The evaluation results indicate that the GPT-based evaluation system achieves a high level of accuracy in grading student submissions. The grades generated by GPT show a strong correlation with the expert-annotated grades, demonstrating its potential as a reliable evaluation tool. Moreover, the automated nature of the system ensures consistent grading across multiple submissions.

GPT exhibits promising capabilities in identifying common programming errors made by students. The model's language understanding, and generation abilities enable it to recognize incorrect syntax, logical flaws, and inefficiencies in the submitted code. By providing specific feedback on these errors, GPT helps students understand and rectify their mistakes.

The feedback generated by GPT demonstrates relevance, coherence, and educational value. The model not only identifies errors but also provides constructive suggestions and explanations to guide students toward improvement. The generated feedback offers personalized insights into each student's performance and highlights areas for further development.

Thus, we compared the efficiency and effectiveness of the GPT-based evaluation system with traditional manual grading. The automated nature of GPT significantly reduces the time and effort required for evaluation, providing timely feedback to students. Furthermore, the consistent grading and detailed feedback generated by GPT contribute to a more objective assessment process. However, during GPT evaluation process, we encountered some challenges, as there was a difference between grades bigger than 3 points, and it was necessary to explain again the requirements with more details. Because of this, we came up with the conclusion that, at this point, GPT can only assist on this process, it should not be used to take a decision independently. For future investigation, OpenAI announced that GPT-4, which is in private preview at this time, has more powerful models for mapping the prompt with dataset, so this conclusion may apply only to GPT.

6. Conclusions

The results demonstrate the accuracy, efficiency, and effectiveness of the GPT-based evaluation system. The automated nature of the system reduces the burden of manual grading while providing timely and personalized feedback to students (Radford, 2019). Future work could explore the integration of GPT within educational platforms, allowing for seamless and scalable evaluation of programming skills.

Integrating GPT into student evaluation has the potential to revolutionize the educational landscape. By streamlining the assessment process, providing personalized feedback, fostering critical thinking, and promoting inclusive education, professors can create a more efficient, engaging, and effective learning environment. As AI continues to advance, educators must embrace these transformative technologies to maximize the potential of every student.

Further research and collaboration between academia and AI developers are necessary to address the challenges and harness the full potential of GPT in schools. To summarize, the educational field holds significant potential, as evidenced by the various approaches to automated programming learning applications. However, our goal is to develop an assisted eLearning system that offers personalized information through engaging interactive activities and creative content.

Our primary objective is to construct a sophisticated eLearning system that assists students in their educational journey. Numerous statistics have repeatedly demonstrated the need to leverage new technologies to enhance our overall quality of life, including education. Therefore, we have devised two distinct components for computer-assisted education.

We envision the assisted education system as a puzzle with multiple interconnected pieces. By implementing the solution for GPT, we have only a small part of this puzzle done. However, there are still some missing pieces to complete the puzzle. Extensive studies have indicated a significant correlation between learning style and eLearning, and students' motivation is crucial for improved learning outcomes(Anderson et al., 1986). Furthermore, as we integrate a vast amount of data into our resources, optimal system performance becomes a critical consideration ((PDF) Intelligent tutoring systems for programming education: a systematic review, n.d.). Looking ahead, we will continue our investigation into how computer technologies can further enhance the field of education in Romania.

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