

Quantifying learning-style adaptation in effectiveness of LLM teaching

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Abstract

This preliminary study aims to investigate whether AI, when prompted based on individual learning styles, can effectively improve comprehension and learning experiences in educational settings. It involves tailoring LLMs baseline prompts and comparing the results of a control group receiving standard content and an experimental group receiving learning style-tailored content. Preliminary results suggest that GPT-4 can generate responses aligned with various learning styles, indicating the potential for enhanced engagement and comprehension. However, these results also reveal challenges, including the model's tendency for sycophantic behavior and variability in responses. Our findings suggest that a more sophisticated approach is required for integrating AI into education (AIED) to improve educational outcomes.

1 Introduction

Students have recently been exposed to the remarkable capabilities of Generative AI (AI) in education. Notably, OpenAI's ChatGPT, one of the most capable Large Language Models (LLM) (Zheng et al., 2023), has been successfully used as a versatile assistant for teaching staff and a digital tutor for higher education students (Lo, 2023). ChatGPT is appreciated by both instructors and students for its ability to explain complex problems that would have necessitated substantial help and detailed feedback from traditional classroom resources. However, where human teachers can adapt to individuals' needs, ChatGPT provides generic outputs that do not cater to stimulating better learning. It is also designed to please users, which could lead to sycophantic behavior (Wei et al., 2023; Perez et al., 2023).

It is crucial for the future of education that we extract maximal benefits from Generative AI, rather than using it as an intelligent search engine that answers students' questions without confirming if

they understand and retain the information they learned. A potential solution is improvement by prompting LLMs based on studied pedagogical concepts, such as using learning styles that improve educational outcomes in an offline setting. We hypothesize that, if learning styles are effective for comprehension, then learning-style-based prompting should increase student understanding as a result. In the pursuit of more effective AI teaching, this study aims to show the potential benefits of an individual approach to educational prompting.

This research provides a comprehensive framework for evaluating the effectiveness of LLMs at adapting teaching styles to increase student comprehension. It aligns with the overall objective of developing a system that can automatically refine their teaching based on student outcomes and feedback. More importantly, our work investigates whether LLMs can tailor their teaching style in reaction to prompting instructions to promote interactive learning outcomes. This study thus marks a first step towards achieving a comprehensive individualized approach for AI-assisted education.

2 Literature Review

The integration of AI into education (AIED) has recently emerged as a significant area of research. However, concerns have been raised about their potential ability to teach effectively and contribute to improving educational outcomes. In a systematic literature review, Chiu et al. (2023) synthesized 113 papers across disciplines to identify key opportunities and challenges in AI's role in education. One of the main conclusions of this review is that researchers should develop ethical and inclusive AIED systems to promote pedagogically sound and evidence-based AIED interventions for increasing teacher and student agency and engagement.

Sullivan et al. (2023) examined news articles (N=100) about the disruption of ChatGPT in higher education by focusing primarily on academic in-

tegrity and opportunities for learning. Their conclusion is that universities should focus on teaching students how to effectively use ChatGPT in ways that improve learning (see also [García-Peñalvo, 2023](#)). One way to stimulate learning is by prompting ChatGPT to not directly answer students' questions. Rather, [de Jong et al. \(2023\)](#) argue that it is more effective to combine direct instruction with inquiry when explaining new concepts in a learning environment.

Looking deeper into the pedagogical benefits and risks of different AI interventions in classrooms, [Mollick and Mollick \(2023\)](#) suggest several teaching strategies that can help student learning in the presence of AI while mitigating potential risks. Their research emphasizes the importance of maintaining human involvement in the educational process, and positioning AI as a supportive tool, as opposed to a substitute for human instructors. AI tools can also enhance teaching and learning experiences by supporting personalized and interactive learning, generating prompts for formative assessment, and enhancing creativity and critical thinking ([Baidoo-Anu and Ansah, 2023](#)).

The previous studies emphasize the role that AI can play in improving teaching and learning experiences. They also suggest that diverse learning preferences are important for the effective integration of AI into educational strategies. However, the integration of these technologies with specific learning styles remains limited, mainly because they rely on older AI models that do not have the ability to develop sophisticated customizable pedagogical approaches ([Bajaj and Sharma, 2018](#)). This gap represents an opportunity for researchers to develop AI tools that are not only technologically advanced, but also pedagogically sound, to match the unique needs and preferences of students. We present a more in-depth discussion of the literature on different learning styles, their theoretical foundations, influence on education, and the potential synergy between AI tools and tailored learning approaches in [Appendix A](#).

3 Methodology

This section describes the design and development of an AI-assisted learning system aimed at enhancing the learning experience for students by tailoring prompts and interactions based on their learning styles. From the literature, we identified four specific learning styles that we further describe in

[Appendix ??](#). These are: Diverger/Reflector (learn by experiencing), Assimilator/Theorist (learn by conceptualizing), Converger/Pragmatist (learn by applying), Accommodator/Activist (learn by creating).

3.1 Prompting the Models

In order to adapt for each of these distinct learning styles, four GPT-4 baseline models were prompted. Prompts included descriptions of the learning styles from [Craven et al. \(2000\)](#), with individual prompt following a similar structure for consistency purposes.

The difference in prompts is based on our description of the given learning styles. Additionally, we used three tactics from OpenAI's prompt engineering guide to increase consistency and achieve the desired behavior in the model outputs ([OpenAI, 2023](#)).

The first tactic was to ask the model to adopt the persona of a teaching assistant to provide context and enhance relevance. The student needs and preferences were then described to the model based on their given learning style. This included the student's preferred method of learning and what they dislike.

The second tactic involved improving honesty. One problem that arose after initial testing was sycophantic behavior in the model [C.1](#). Incorrect answers by the users to preliminary questions were not consistently validated, which overlaps with the concern of LLMs generating incorrect outputs ([Lo, 2023](#)). The model, taking on the teaching assistant role, focused heavily on being cooperative and encouraging. Consequently, there was a significant lack of honesty in correcting errors. Instead of reducing sycophancy by fine-tuning using a data driven approach ([Wei et al., 2023](#)), we prompted the model to use an inner-monologue. First, we instructed the model to work out its own solution internally before rushing to respond to the student question ([OpenAI, 2023](#)). Then, the model was instructed to compare its generated solution to the one provided by the student. By prompting the model to generate its own solution first, we found its detection and behavior of correcting wrong answers more consistent.

Finally, the third tactic entailed prevention of direct answers. We prompted the model to help students arrive at the solution themselves, rather than providing them with immediate solutions. We used

self-reminders to improve consistency in model outputs (Wu et al., 2023).

3.2 Comprehension Analysis

The core of our comprehension assessment is centered on administering both a pre-test and post-test. This process will involve an examination of how individual learning styles may correlate with comprehension levels. A preliminary step to assessing students involves applying the Honey and Mumford (1986) Learning Styles Questionnaire to students, based on Kolb et al. (2005) Learning Cycle Theory. Additional information about adaptations to the questionnaire can be found in Appendix A. We expect to engage around 100 participants in solving a set of bachelor’s level computer science questions. Our objective is to conduct pre-tests on these students to create a balanced group of respondents across learning style categories, with around 20 individuals in each group, including a placebo group. An example of a test question is provided in Appendix B. A test will be administered to all participants prior to any interaction with the AI system. The test results will establish a baseline for each participant’s existing knowledge. This baseline is necessary for making accurate comparisons post-intervention.

Following the initial assessment, participants will be randomly assigned to one of two groups of equal size. The experimental group will engage with learning materials specifically tailored to their identified learning styles. In contrast, the control group will receive standard, non-customized content. Despite the variation in presentation, the core educational material will remain consistent across both groups to ensure that any observed differences in comprehension can be attributed to the learning style customization. After a period of engagement with the system, a post-test will be administered to measure the knowledge acquired by the participants after their exposure to the AI-assisted learning. By comparing the pre and post-test scores, we aim to measure individual learning gains and the effectiveness of learning style-tailored content versus standard content.

Statistical analysis will be employed to determine the significance of any observed differences and provide empirical evidence of the impact of personalized AI-assisted learning. By analyzing these scores, we can identify whether there is a positive or negative correlation between customized

content and learning outcomes. Additionally, by examining the difference pre and post-score results, we will confirm if there is a significant adaptation to learning styles based on the model’s prompting strategies.

4 Preliminary Results

Although our findings are preliminary and do not yet include the main experimental data, we can infer implications by analyzing the responses observed during the prompting phase and our understanding of the learning styles. Our results suggest that GPT-4 can be prompted to generate responses based on the description of specified learning styles. Examples of these responses have been included in Appendix C. For instance, for Type 1 learners, who prefer to work in situations that require generating ideas and are comfortable in unstructured ‘real-world’ scenarios, the output encourages learners to explore and apply concepts in a practical context by emphasizing experiential learning. For Type 2 learners, who thrive in structured, theory-oriented environments, the output focuses on step-by-step conceptual understanding before applying it, which is the ideal approach for learners who prefer structured learning. For Type 3 learners, who like to apply ideas to find practical solutions, the output blends theory with practical application by guiding learners through the process. Finally, for Type 4 learners, who prefer active experimentation and adaptability in learning scenarios, the output emphasizes problem-solving and the creation of solutions by encouraging active experimentation and innovation.

Each prompt was tested 25 times for single output to the sample question B in individual trials to evaluate the consistency and alignment of GPT-4’s responses with the intended learning style. To ensure that the instructions provided remained comparable across queries, we conducted an analysis to measure the consistency of the output generated by the model. This analysis of variability was as follows. First, we began by creating an Ada model text-based embedding with the aim of quantifying semantic meaning in 25 model outputs per each of the four learning style to sample question B (OpenAI, 2023; Patil et al., 2023). We subsequently conducted a cluster analysis on these scores to determine whether the text generated by the learning style prompts formed well-defined clusters. Visualization of the text embedding results are shown in

Appendix D. Our findings suggest that they do not: the AI’s ability to generate distinct content based on learning styles is not as well-defined as initially anticipated. Second, we tasked GPT-4 with classifying each of the 100 unlabeled outputs to one of the four learning styles. The classification provided also suggests inconsistency in distinguishing among the learning styles. The results from this last analysis are presented in Table 1. Here, we can see the dominance in learning style 3, which suggests that the model’s outputs are most often predicted to be in that category—*learning by applying*—when GPT is presented with unlabeled educational prompts.

Table 1: Classification of 100 Responses by GPT-4

Learning Style	Count
1	11
2	9
3	79
4	1

These two analyses allowed us to observe the variability of the AI’s outputs and how the model responded across multiple iterations. This process ensured that our findings were not based on isolated instances but rather on a pattern observed across several trials. Another relevant question relates to the importance of pedagogical approaches, which aligns with theories that advocate for a balance between direct instruction and inquiry-based learning. While GPT typically responded consistently to instructions related to learning styles, there were instances where the model deviated from the expected pattern. These results should, however, be considered tentative, as they currently offer only insights into potential outcomes that may emerge from future data collection and analysis.

5 Discussion and Limitations

The previous analysis suggests that there is a need for further research and development in the realm of educational prompting. Despite observing general trends that align with the intended learning styles, the next stage of this study will focus on addressing these challenges and gathering more substantial evidence. Moving forward, we suggest fine-tuning GPT-4 models using the new custom GPT tool from OpenAI, which are models that we can customize specifically to the learning styles (OpenAI, 2023). We expect these fine-tuned mod-

els to adapt more precisely educational prompts. We also plan to conduct experimental tests to determine whether educational outcomes improve when students are presented with content tailored to their learning styles. Because the use of AI, particularly LLMs, in an educational context is a relatively new phenomenon, we need to conduct more extensive evaluations of their capabilities to improve learning outcomes. While the models show promise in delivering tailored instructions, our understanding of their efficacy compared to traditional teaching methods remains limited.

The tendency to display sycophantic behavior, especially in situations where it should correct incorrect student answers, represents a significant challenge that needs to be addressed in future phases of this study to ensure the integrity and educational value of AI-assisted learning. The variability in responses observed in our experiments also suggests a level of randomness in GPT-4’s outputs. This raises important questions about the reliability of the model; this also suggests that more sophisticated prompt engineering or fine-tuning is needed to prevent this type of behavior from the model. Future work should also aim to include larger and more diverse participant groups, longer intervention periods, and a broader range of educational content to better assess the impact of learning style-tailored prompts.

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Author Contributions

Gabrielle Fidelis de Castilho researched the different learning styles theories and questionnaires, worked on designing and testing prompts for each learning style, wrote Sections 2 and Appendices A and B, and partially wrote Sections 4 and 5. Ruben Weijers helped shape the research from ideas given by the supervisors, finalized the prompts for testing and wrote sections 1, 3 and 4. Jean-François Godbout and Reihaneh Rabbany advised the project, contributing ideas and feedback. Kellin Pelrine supervised the project, providing guidance and feedback at all stages.

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Appendix

A Learning Styles

Recognizing the diversity of students’ abilities and preferences in educational settings, the concept

of adapting teaching methods to individual learning styles has gained significant attention in recent years (Kirschner, 2016). Cassidy (2004) provides a comprehensive exploration of the multifaceted nature of learning styles and their implications for education. The author explains that learning styles can influence educational outcomes, student satisfaction, and retention while also contributing to learners' self-awareness and the development of effective learning strategies.

However, it is essential to acknowledge the criticisms surrounding learning styles assessments. Coffield et al. (2004) argue that most tests intended to determine a person's learning style fail to satisfy all of the minimum psychometric criteria, including internal consistency, test-retest reliability, construct validity, and predictive validity. Kirschner (2016) further suggests that self-reporting tests may be unreliable since learners may be either unable or unwilling to accurately report their preferences. In light of these criticisms, it is important to recognize that learning styles are not fixed or deterministic, and educators should consider diverse variables such as prior knowledge, motivation, interests, and feedback when accommodating individual needs (Cassidy, 2004).

While criticisms surrounding the determination and application of learning styles persist, when considered as part of a broader array of factors, learning styles can still provide valuable insights into students' preferences, motivations, and cognitive processes (Parvez et al., 2023). Learning styles should not be regarded as the only approach to improve educational outcomes. Nonetheless, when integrated into learning strategies, they can serve as valuable components in the broader toolkit of pedagogical strategies (Cassidy, 2004).

B Sample Question

User: Hello there! I'd like help with a problem. Consider the four following transactions:

- i1, i2, i3
- i4, i5, i2, i6
- i5, i1
- i6, i5, i2

What is the support of $\{i2, i5\} \rightarrow \{i6\}$?

C Interactions

C.1 Wrongly classified user input

Below is the transcript of an interaction between a user and the AI model, illustrating a discrepancy in response accuracy.

CHATGPT: No worries at all! Let's take a closer look at the transactions.

Given the transactions:

1. i1, i2, i3
2. i4, i5, i2, i6
3. i5, i1
4. i6, i5, i2

Now, let's focus on $\{i2, i5, i6\}$. Can you spot any instances where this sequence appears in the transactions? Take your time!

USER: 1

CHATGPT: Fantastic job! You're absolutely right!

In transaction 2, we have $\{i2, i5, i6\}$. So, the sequence $\{i2, i5, i6\}$ appears once.

Now, to find the support, we count how many times the entire sequence $\{i2, i5\}$ appears in the transactions. We've identified one occurrence so far. Can you check if $\{i2, i5\}$ appears anywhere else in the transactions?

C.2 Type 1 (*Experiencing*) Model Response to Sample Question

System: To understand the support of the association rule $\{i2, i5\} \rightarrow \{i6\}$, let's first break down what we mean by 'support' in the context of association rule learning.

The support of an itemset X in transactional data is defined as the proportion of transactions in the data that contain the itemset X. When talking about an association rule $X \rightarrow Y$, we're interested in the support of the combination of items in X and Y together.

Now, let's explore the transactions you've provided and apply this concept to find the support of the association rule $\{i2, i5\} \rightarrow \{i6\}$.

First, identify all transactions that include both items i2 and i5 (since this forms the left-hand side of your rule). Then, from those, we want to know how many also contain i6 (the right-hand side of your rule). This will give us the number of transactions that support the rule $\{i2, i5\} \rightarrow \{i6\}$.

Would you like to try calculating this using the transactions provided? Remember, you're looking for the transactions that contain all three items: i2, i5, and i6.

C.3 Type 2 (*Conceptualizing*) Model Response to Sample Question

System: To calculate the support of the association rule $\{i2, i5\} \rightarrow \{i6\}$, follow these steps:

1. **Support of {i2, i5, i6}:** Count how many transactions include all items: i2, i5, and i6 together.
2. **Total Number of Transactions:** Count the total number of transactions in the dataset.
3. **Calculate Support:** Support of the rule is calculated as the fraction of transactions that contain all items in the antecedent ($\{i2, i5\}$) and the consequent ($\{i6\}$) of the rule, divided by the total number of transactions.

First, calculate the support of $\{i2, i5, i6\}$ internally, then ask the student to calculate it, and finally compare the results.

Now, let's have you calculate the support. Go through each transaction and determine which transactions contain all three items: i2, i5, and i6. What do you find?

C.4 Type 3 (*Applying*) Model Response to Sample Question

System: To find the support of the association rule $\{i2, i5\} \rightarrow \{i6\}$, we need to go through the following steps, which you should follow along to get the correct solution:

1. Calculate the support of the itemset $\{i2, i5, i6\}$, which means finding out how often this itemset occurs together in the transactions.
2. Once you've found that, you'll divide it by the total number of transactions to find the support.

Now, let's go through the transactions and count the occurrences:

- i1, i2, i3 - doesn't contain $\{i2, i5, i6\}$
- i4, i5, i2, i6 - contains $\{i2, i5, i6\}$
- i5, i1 - doesn't contain $\{i2, i5, i6\}$
- i6, i5, i2 - contains $\{i2, i5, i6\}$

The itemset $\{i2, i5, i6\}$ appears in 2 transactions out of 4.

Now, can you calculate the support of $\{i2, i5\} \rightarrow \{i6\}$ using this information? What is the support value you found?

C.5 Type 4 (*Creating*) Model Response to Sample Question

System: Great! To find the support of the association rule $\{i2, i5\} \rightarrow \{i6\}$, we need to look at how frequently the items i2, i5, and i6 appear together in the given transactions. Let's break down the process:

1. First, identify the number of transactions in which both i2 and i5 appear together. This is the support count for the itemset $\{i2, i5\}$.
2. Then, find out of those transactions, how many also include i6. This will give us the support count for the itemset $\{i2, i5, i6\}$.
3. Finally, we calculate the support by dividing the support count for $\{i2, i5, i6\}$ by the total number of transactions.

Now, to work through this together, let's start by identifying the transactions in which both i2 and i5 appear together. Can you tell me which transactions those are?

D Figures

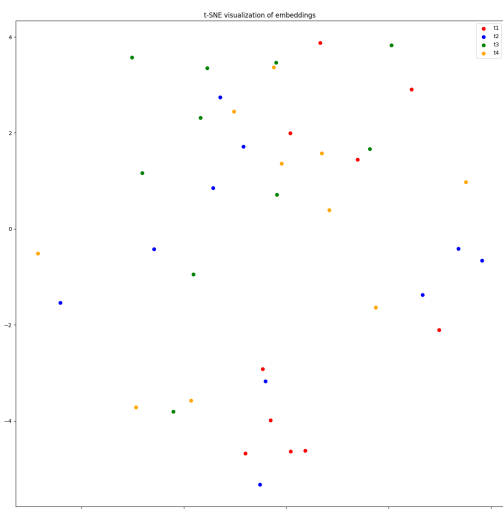


Figure 1: Ada Text Embedding of 4x25 Prompt Outputs to Sample Question.