Exploring the Use of GPT-4 in Co-creating Personalized Case Scenarios for Higher Education.

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Abstract

In the fast evolving landscape of Artificial Intelligence in Education (AIEd) Large Language Models (LLMs) like GPT-4 have emerged as powerful and versatile tools capable of adapting for a wide set of natural language tasks. This study explores into an interaction design where higher education students utilized GPT-4 to craft personalized case scenarios tailored for their coursework. This process not only facilitates tailored learning experiences, but also engaged students into speculative reflections about the potential futures of AIEd .... Add up on results and conclusions when done

Keywords: ChatGPT, Large Language Models, Higher Education, Human-AI Co-creation ,Personalized Learning, Speculative Scenarios

1 Introduction

Upon every technological breakthrough, the educational domain reconsiders its methods and strategies. During the recent decades, the rise of digital technologies has reshaped the educational landscape. Evidence from the past 40 years on educational technologies impact consistently indicates positive benefits from its integration in programming courses or through innovative approaches (Higgins et al., 2012). However, while digital technologies might spark motivation and engagement in young students, its mere adoption does not ensure favorable outcomes. To fully embrace their potential, a deliberate pedagogical approach is essential, especially when transitioning from traditional to modern educational approaches (Khaddage et al., 2021; Parker et al., 2020) .

As part of the larger digital transformation, Artificial-Intelligence (AI)-based systems have emerged as important players in the educational domain. These systems have found extensive use in administration, instruction, and learning (Chen et al., 2020), accompanied by a growing body of research around AI in Education (AIEd), a distinct sub-field of digital learning research (Niemi et al., 2023). But despite the wide range of potential applications of AI-based systems, they have been mostly implemented to facilitate, or automate, mainstream learning approaches. While useful, this approach sidelines teachers agency, experience, and creativity to integrate such technologies into their unique practices and pedagogical designs. (Holmes et al., 2023)

A dominant trend has been that AIEd implementations are predominantly designed by technical teams or departments, such as those focused in Science, Technology, Engineering, and Math (STEM), leading to a notable under-representation of educational or psychological perspectives in AIEd research (Holmes & Tuomi, 2022; Zawacki-Richter et al., 2019). Among the probable causes of this we can highlight the lack of technical expertise, among others, which is a big barrier for educational adoption of technologies (Reid, 2014). However, as with other digital technologies, AI systems are evolving to become more accessible by reducing their technical entry barriers, both for casual use and for the design of new applications.

One of such evolution are Large Language Models (LLMs) such as OpenAI's Generative Pre-Trained (GPT) model. They have significantly evolved into systems capable of performing various natural language tasks (Brown et al., 2020). Interestingly, they have shown emergent features as they are able to perform tasks that were not originally part, or expected, of the design (Wei et al., 2022). For example, GPT-3 could adapt to new tasks using an approach known as *In-context learning*—relying on natural language descriptions of the task—an ability that it's predecessor struggles to perform consistently (Brown et al., 2020; Wei et al., 2022). This adaptation for different tasks, without requiring exhaustive re-design of their architectures, combined with their potential to serve as building blocks for task-specific AI-tools has led to some researchers to classify them as foundational models (Bommasani et al., 2022; Eloundou et al., 2023). Furthermore, its last iteration (GPT-4) brought a significant increase in performance across every measured metric (OpenAI, 2023a). These capabilities present wide opportunities in both design and application. Given that state-of-the-art models do not require advanced technical programming skills, professionals from different domains might now tailor customized tools that align closely with their contexts, needs, and specialized approaches (Cain, 2023). Building on this accessibility, OpenAI has recently announced the upcoming "GPT builder", which will enable users to tailor specific web-based GPT applications for private or shared use (OpenAI, 2023b, 2023c). Altogether, a new generation of commercial, public, and private LLMs-based AI applications is on the horizon, with many speculated to be significant in shaping the near to mid-term future (Bommasani et al., 2022; Bubeck et al., 2023).

Due to its versatility and accessibility, OpenAI's "ChatGPT" has become the fastest-growing application in history since its launch on late 2022 (Milmo, 2023). As a conversational chatbot, it uses natural language processing to understand and generate human-like text in a dialectical fashion. By providing certain input (prompts) ChatGPT can answer different kinds of questions. Additionally, by using advanced prompting methods users can improve its performance in a wide range of tasks (Fernando et al., 2023; Wei et al., 2023). Potential educational uses involve teaching preparation (generation of course materials, providing suggestions); Assessment (generation of exercises or case scenarios, providing feedback); Learning support (answering questions, summarising information) among others (Lo, 2023; Montenegro-Rueda et al., 2023). However, educational research remains sparse and focuses predominantly in theoretically exploring its potential and limitations (Cain, 2023; Qadir, 2022), and assessing its performance on traditional assessment methods (Nisar & Aslam, 2023). Due to its novelty, a gap in exploratory empirical studies is evident.

We focused our study on exploring the interaction between students and GPT-4 for the creation of personalized course materials in a higher education doctoral course. Our research not only aims to pave the way for innovative designs that enrich and personalize in-person learning experiences using AI tools but also to inspire deeper exploration into the vast potentials of integrating AI in educational settings.

Approach

The study was conducted in an on-campus doctoral course titled "Basics of AI in education", aimed at exploring historical and contemporary AIEd developments. We covered an overview of the historical technical evolution of AIEd systems, examination of current popular systems, like performance predictors, AI-tutors and LLMs, a review of the intersection between AI and cognitive sciences, as well as a discussion of emerging ethical concerns and regulatory developments.

We designed the course assignments to explore hypothetical scenarios about AI implementations in education. For this purpose the students were asked to individually design a study, and write a reflective essay about a specific chosen scenario. Consequently, the course topics were broad and suggestive, not focused on any pre-defined scenario, giving the students freedom to choose a scenario of their own interest. Complementing the course contents with a practical experience, we guided the students to interactively generate their hypothetical scenarios with the support of AI.

To facilitate this, we designed a guided interaction to co-create personalized hypothetical scenarios through GPT-4, which involved pre-defined *prompt templates* and a *set of keywords* to construct scenario generation prompts. We guided our design to address two main objectives.

Firstly, to accommodate students with diverse levels of experience with ChatGPT. Due to its novelty, we had to guide students without experience in interacting with ChatGPT before. By providing clear guidelines and a set of actions to choose from, outlined by prompt templates, we expected that students lacking prior experience could complete their co-creation task without major technical challenges. Secondly, to enable a systematic and reproducible examination of interactions with ChatGPT by establishing a controlled interaction protocol. Not only it standardizes how students interact with ChatGPT but it can be tailored to capture specific elements according to our research interests, particularly the behavioral dimensions of students interaction.

Upon reflecting on the conversational dynamics of ChatGPT in the context of our scenario co-creation task, we opted to guide our prompt design with insights from behavioral models used in Information Foraging Theory. Given that ChatGPT has contextual memory of the conversation, it enables not only to generate scenarios but also to delve deeper by prompting for additional details, thus enriching the scenario with more information. This dynamic closely mirrors two core aspects of Information Foraging Theory: *Exploration*, where new information landscapes are searched (scenarios), and *Exploitation*, where agents decide to utilize a landscape to its fullest potential—in this case, further elaborating an interesting scenario.(Cohen et al., 2007; Hills et al., 2015; Todd & Hills, 2020). Therefore we shape our prompt design around these distinct foraging actions, conceptualizing the interactions as an information foraging task.

Furthermore, we deemed worthy to focus our analysis in examining the role of Computational Thinking Skills in modulating students interactions with ChatGPT. In a seminal contribution, Wing (2006) underscored the importance of Computational Thinking skills, which enables people to solve tasks in a similar way that computer algorithms work and are beneficial across most professional domains. Since then, Computational Thinking Skills have grown into a cornerstone of research in digital education and different researchers argue that they correlate with more confident and efficient use of digital technologies (Cansu & Cansu, 2019; Grover & Pea, 2013; Shute et al., 2017).Regarding its influence over Human-AI Interactions, Celik (2023) explored the determinants of AI literacy, which encompass the knowledge for using, recognizing and evaluating AI-based tools, and reported a significant correlation with Computational Thinking Skills. Building on these contributions, we aim to delve deeper into the practical manifestations of such association and investigate whether the unique nature of LLMs, distinct from other AI systems, might reveal new insights into Computational Thinking Skills within the evolving landscape of education.

Therefore, in our study we focused our analysis in exploring the following aspects.

RQ1. How does the students' Computational Thinking Skills influence their information foraging behavior when co-creating scenarios with GPT-4?

Alternatives:

(i) Through which behaviors do students showcase their Computational Thinking skills during their engagement with GPT-4?

(ii) How are students' Computational Thinking skills reflected in their interactions with GPT-4?

(iii) In what ways do students demonstrate Computational Thinking skills when engaging with GPT-4 in a structured setting?

Note, alternatives chosen by a set of alternatives co-created with GPT-4

2 Methods

Guided Interaction Design

As mentioned above, our design aims to orient the participants in their interaction and enable a methodical analysis of the process. It consists of six modifiable *prompt* *templates*, divided in two types; a set of *keyword cards*, individual cards with relevant concepts; and an *interaction protocol*, outlining each interaction process. With them, participants crafted a diversity of prompts tailored to their interests, which we used to create and elaborate their hypothetical scenarios in ChatGPT.

Prompting Templates and Set of Keywords

We created the prompt templates by distinguishing two main categories, following the information foraging theoretical approach described above.

Firstly, we created three different *Exploration prompts* aimed at creating unique scenarios. Their nature was defined by their start (”Describe to me a scenario...” and ”Predict a future scenario...”) and they allowed for the combination of a maximum of 6 keywords, which granted sufficient conceptual context for our co-creation aims. They provided the starting point to create and explore different scenarios and informational landscapes.

Secondly, we created three *Exploitation prompts* to further elaborate already generated scenarios. They prompted for more information about the specified scenario, focusing in one, or two, keywords of interest. Therefore, they enabled the exploitation of an interesting scenario for more information.

This distinction between the two types of *prompt templates* facilitates our analysis by enabling us to clearly categorize their use within the interaction as either *exploration* or *exploitation* actions.

To construct the *set of keywords*, we envisioned seven categories that generally described AI-influenced educational scenarios. These categories were: Effects, Actors, AI Tools, Educational Process, Environment, Subject, and Activity. Afterwards, aiming of examining the participants' personal interests in driving the interaction, these categories were populated based on an initial course assignment, in which participants were asked to outline their interests in relation to the aforementioned categories. Additionally, by taking into account the role of their reported interests, this fostered a student-driven approach that might enhance the relevance and engagement of the participants within the task. As a result, we created a set of 86 keywords distributed unevenly in the different categories. They provided the conceptual context of every generated scenario, according to the participants' choices and combinations of them.

Furthermore, we allowed the participants to use keywords provided by ChatGPT. After observing the nature of its answers to our prompts, where ChatGPT generally offered bullet points to describe the main aspects of the generated scenario, we found interesting to allow the use of its points headers as keywords. These *GPT-sourced keywords* enabled more flexibility and precision, particularly if participants were prone to exploit an interesting scenario based on its specific conceptual information, which would not be necessarily present in the *keywords set.* This added another interesting layer of theoretical depth, as we could observe how the *Exploration* and *Exploitation* of information intertwined with both human-generated concepts and AI-generated concepts.

Both the *prompt templates* and the *keywords* were later printed and laminated. The *prompt templates* consisted of a fixed text written in black representing unchangeable elements, along with variable spaces written in colored texts. These colored spaces corresponded to the different categories where participants could select and combine various concepts given by the *set of keywords.* The keywords were represented as a series of color-coded cards, each card corresponding to an individual keyword and colored by category. The color-coding matched the ones used for the *prompt templates*, to enable a more intuitive understanding of the allowed combinations.

To facilitate the interaction process, we designed an *interaction protocol* to guide the use of the *prompt templates* with the *set of keywords.* This protocol guided the process, standardized my role as a researcher, and constrained my influence over the participants' decision-making process. This approach ensured sufficient space for participants' agency in driving the interaction, while maintaining a helpful guidance throughout the interaction.

Interaction Protocol

The interactions were realized individually with each participants. The main author acted as intermediary between the participants and ChatGPT, guiding them over the co-creation process according to the following interaction protocol:

- Prompting templates were displayed in a table, all of the options visible for them. The keywords cards were facing down, distributed almost equally in 5 rows and divided by category.
- I reiterated the aim of the task—creating an interesting scenario for their assignments—and introduced the purpose of the prompting templates and the set of keywords. Additionally, I provided an example of a generation prompt that included example keywords. I reminded their uses constantly during the interaction to ensure they could effectively engage with the task.
- When the aim and rules were clear, participants proceeded to uncover the first row of cards and started crafting a prompt by selecting one template and keywords of interest. When completed, I prompted ChatGPT and displayed the generated text. After participants finalized reading, I reminded them their different choices, either generate (*explore*) other scenarios, further elaborate (*exploit*) the generated scenario, or end the task by choosing the scenario in front of them. I also pointed out the possibility of using GPT-sourced keywords to explore or exploit scenarios, similar to the physical cards.
- When the participant found that a scenario was interesting enough for them to choose it and end the task, the full transcript of the conversation for the selected scenario was provided to them. After the scenario was provided, the participants continued to work into their assignments, focused in their chosen scenarios.

Computational Thinking Scale

Following our purpose of examining the role of Computational Thinking within our interaction process, and following Celik (2023) previous study on AI literacy, we decided to use the same data collection instrument, the Computational Thinking Scale (CTS) survey.

Developed by Korkmaz et al. (2017), it is a self-report scale based on the framework by CSTA & ISTE (2015), and the Computational Thinking Leadership Toolkit ISTE

(2011). They define computational thinking as the result of 5 intertwined skills, Creativity, Algorithmic Thinking, Cooperativity, Critical Thinking, and Problem Solving. Consequently, the scale consists of 29 items divided in the corresponding 5 sub-factors. Based on a five-point Likert-ype rating structure, with higher scores indicating greater development of computational thinking skills.

Additionally, considering that the scale was developed in computer sciences learning environments we adapted three items, aiming for more contextual clarity in grammar and semantics. We adapted mathematically specific terms to be more generally understood. We deemed this adaptations suitable for our distinct educational environment.

2.1 Data Collection

The interaction and survey data was collected from ten participants who enrolled into "Basics on AI in Education" doctoral course at the University of Helsinki. Eight of them were doctoral students and two master students, all of them involved in educational research. A majority of them were Finnish, but the course activities were done in English as the course is part of the international doctoral programme. Their previous experiences with ChatGPT, or AI, differed. While most had extensive experience and were constantly using ChatGPT in their workflow, others had not interacted with ChatGPT before the course.

2.2 Data Analysis

Frequency based coding in Atlas.ti.

Descriptive analysis realized for interesting patterns noticed while overviewing the data

Network analysis to find significant associations between variables.

3 Results

4 Discussion

Discussions should be brief and focused. In some disciplines use of Discussion or 'Conclusion' is interchangeable. It is not mandatory to use both. Some journals prefer a section 'Results and Discussion' followed by a section 'Conclusion'. Please refer to Journal-level guidance for any specific requirements.

4.1 Limitations

4.2 Further Lines of Research

4.3 Conclusion

Conclusions may be used to restate your hypothesis or research question, restate your major findings, explain the relevance and the added value of your work, highlight any limitations of your study, describe future directions for research and recommendations.

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