ChatGPT-CPS: The Cultivation of Collaborative Problem-Solving Ability through Human-AI Interaction

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Abstract. In the context of technological innovation driving the development of educational technology, collaborative problem-solving (CPS) and innovation skills have become essential core competencies for high-quality talent. The importance of collaborative problem-solving in personal development has also garnered increasing attention from society. However, current educational efforts to develop students' collaborative learning and problem-solving skills mainly rely on teacher-led classroom instruction. From the perspective of the integration of digital and intelligent technologies, this article innovatively shifts the focus to the cultivation of human-AI collaborative learning abilities. It specifically examines how students engage in human-AI collaboration using ChatGPT technology within different knowledge contexts across various learning stages. This study tracks students' mastery of current knowledge points and their collaborative learning processes with ChatGPT, using paired t-tests, independent t-tests, ANOVA, and qualitative feedback analysis to evaluate the impact on their collaborative problem-solving skills. The findings demonstrate that human-AI interaction plays a significant and valuable role in improving students' collaborative learning abilities, providing substantial support for educators in future efforts to cultivate and enhance students' collaborative problem-solving skills in teaching.

Keywords: Collaborative Problem-Solving, Human-AI Interaction, ChatGPT.

1 Introduction

In the contemporary educational context, Collaborative Problem Solving (CPS) is one of the essential skills for 21st century learners and has received a lot of attention from the education community [1]. Current artificial intelligence models have had a positive impact on solving various complex problems. Additionally, intelligent diagnosis models, like the one developed by Yu et al. (2023) for Alzheimer's disease using neural networks, highlight the potential of AI in providing real-time analysis and decision support in complex scenarios [2]. Applying similar AI models to educational contexts can significantly improve the precision and timeliness of student performance monitoring and assessment, thereby supporting the development of CPS skills through human-AI

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collaboration (HAC). Current teaching practices and research methods are still mainly limited to traditional classroom teaching, and two scholars, He Yingzhao and Li Huijia, have integrated knowledge mapping and scholar profiling to select online scholarly resources [3], but have not paid enough attention to real-time monitoring of students' knowledge mastery or tracking their progress on specific knowledge items. As a result, existing methods often lack the precision and efficiency needed to effectively develop CPS competencies.

This study seeks to address these deficiencies by examining the interplay between human-machine collaboration and CPS development, alongside the role of knowledge tracking in enhancing these abilities. Specifically, this research is guided by two central research questions (RQs):

RQ1. What is the impact of Knowledge Graphs and individual knowledge mastery on LLM-generated text?

RQ2. What is the impact of using Knowledge Graphs and individual knowledge mastery on students' interaction with large language models in HAC?

To address these research objectives, this study uses ChatGPT technology to enhance human-machine interaction and systematically explores its potential to improve students' CPS skills. It aims to extend the methodological framework for developing CPS skills and address the limitations of traditional methods for assessing students' mastery of knowledge. The research will produce a comprehensive report on the role of HAC in promoting CPS skills, contributing to educational theory and practice.

2 Literature Review

During these years, in an era marked by the convergence of digitalization, artificial intelligence, networking, and big data, the integration of digital and intelligent technologies is playing a transformative role in advancing CPS frameworks. Advances in fields like 3D semantic understanding, as discussed by Yao et al. (2023), provide a foundation for enhancing real-time student monitoring through intelligent systems, which can fill gaps in traditional pedagogical methods by dynamically assessing students' knowledge acquisition [4]. As we enter the era dominated by intelligent computing, the digital-intelligence fusion of big data, artificial intelligence, cloud computing, digital twins and other technologies will reshape the learning scene [5]. Education has entered an epoch dominated by intelligent computation, wherein technologies such as big data analytics, artificial intelligence, cloud computing, and digital twins are reconstructing learning environments through the fusion of digital intelligence. Furthermore, techniques such as those introduced by Yao et al. (2024), which focus on bird's-eye view object detection, could be adapted to track student interaction with intelligent systems and knowledge graphs [6]. This enables a high-level analysis of student performance across diverse learning contexts, allowing for more accurate and personalized learning pathways. In addition, the work by Yu et al. (2023) on evaluating teacher teaching posture using AI-integration posture recognition illustrates how intelligent technologies can be integrated into educational environments to improve real-time monitoring of both teaching and learning behaviors [7]. This approach reinforces the value of human-machine collaboration in both evaluating and enhancing CPS skills. However, these methods are gradually being promoted and require further exploration.

3 Methodology

In the context of a learning system using a Large Language Model (LLM), Knowledge Graph (KG), individual learner's knowledge proficiency (Pi), prompts (Pr), specific knowledge points (K), and generated text (Text), we can model their relationships through logical formulas representing the interactions between these components. Below is a rigorous academic representation of these relationships.

3.1 Variables and Definitions

- LLM: Large Language Model, which processes inputs and generates responses based on knowledge.
- KG: Knowledge Graph, representing the structure and relationships between knowledge points.
- Pi: Personal Knowledge Proficiency, representing an individual's mastery level of a specific knowledge point.
- Pr: Prompt, the input given to the LLM that includes context and questions related to knowledge points.
- K: Specific Knowledge Points in the knowledge graph.
- Text: The output generated by the LLM based on the input prompt and knowledge graph.

3.2 Formula Representation and Relationships

The formula representation and relationships can be described as:

$$\forall x(\mathrm{Text}(x) \leftrightarrow \exists y(\mathrm{LLM}(y,\mathrm{Pr}(x),k(x)) \wedge \mathrm{KG}(y,\mathrm{Pi}(x),k(x)))) \tag{1}$$

where $\forall x\,(\mathrm{Text}(x) \leftrightarrow \ldots)$ represents every instance of generated text xxx, the existence of the text is logically equivalent to satisfying certain conditions, $\exists y(\mathrm{LLM}(y,\mathrm{Pr}(x),k(x)) \wedge \mathrm{KG}(y,\mathrm{Pi}(x),k(x)))$ exists a specific large language model y that processes the prompt Pr and the knowledge point k, while also considering the interactions between the knowledge graph and personal mastery, $\mathrm{LLM}(y,\mathrm{Pr}(x),k(x))$ describes large language model y generates text by taking in the prompt $\mathrm{Pr}(x)$ and the specific knowledge point $k(x)$. This reflects the conventional process of text generation, and $\mathrm{KG}(y,\mathrm{Pi}(x),k(x))$ represents knowledge graph KG, in conjunction with the model y, refines the output based on the learner's mastery level Pi of the specific knowledge point k. This ensures the generated text is personalized and contextually relevant according to the learner’s individual knowledge.

Overall Relationship:

The entire system's relationship can be described as:

$$Text^* = LLM(Pr, P_i, KG, k) \tag{2}$$

However, in most cases, human-AI collaboration often lacks Pi (Personal Knowledge Proficiency) and Pr (Prompt), leading to the following formula.

$$Text = LLM(Pr, k) \tag{3}$$

In the context of human-AI collaborative learning, the relationship between Text, LLM (Large Language Model), Pr (Prompt), Pi (Personal Knowledge Mastery), KG (Knowledge Graph), and k (Specific Knowledge Points) can be formalized using a logical predicate framework. This relationship is governed by the interaction between these elements to ensure that the generated output, Text, is not only based on the input prompt but also dynamically adjusted based on personalized knowledge levels and structured relationships among knowledge points.

4 Experiment

4.1 Experiment Design

The experiment aims to evaluate how the integration of a knowledge graph (KG) and individual mastery level (Pi) into LLM-generated text impacts its quality and enhances collaborative learning among junior high school students.

The hypothesis posits that LLM-generated text incorporating KG and Pi will improve student-human collaboration (H1), while the null hypothesis (H0) suggests no significant difference in outcomes between the text with or without KG and Pi. Sixty junior high students, aged 12-15, with similar proficiency levels, will participate. They will be randomly divided into two groups: the control group, which engages with LLM-generated text without KG and Pi, and the experimental group, which uses text that integrates KG and Pi. Materials include ChatGPT-4o for generating the collaborative text, a knowledge graph (KG) representing domain knowledge, and Pi, which captures each student's mastery of specific knowledge points.

4.2 Experimental Preparation

Students will first take a pre-test to assess their baseline knowledge in a given subject. During the experimental sessions, the control group will collaborate using LLM-generated text based on prompt inputs alone, without the inclusion of KG or Pi. The experimental group will use LLM-generated text that incorporates KG and Pi, allowing the text to adapt to each student's knowledge proficiency and provide contextually relevant support. After collaboration, all students will take a post-test to measure knowledge acquisition and collaborative learning outcomes. Throughout the sessions, interaction quality and student engagement will be observed, and feedback will be collected from both groups regarding the perceived utility of the LLM-generated text.

4.3 Analysis

Quantitative analysis will use paired t-tests for within-group pre- and post-test comparisons, and independent t-tests for differences between control and experimental groups. Collaboration quality, measured by interaction frequency, idea generation, and problem-solving contributions, will be analyzed with ANOVA. Qualitative feedback will assess perceived usefulness of LLM-generated text.

5 Results

This study compared the impact of LLM-generated text on student-to-student collaborative learning, with and without the integration of Knowledge Graph (KG) and Personal Knowledge Proficiency (Pi). The results showed that students in the experimental group using KG and Pi significantly outperformed the control group on several key metrics. Specifically, the experimental group showed improved knowledge retention, increased efficiency in collaborative learning and problem solving, and demonstrated superior knowledge mastery. KG and Pi provided clearer cognitive frameworks that facilitated complex problem solving and encouraged innovative thinking. In addition, the structured knowledge and personalized support provided by KG and Pi not only enhanced the specificity of the learning materials, but also increased student motivation and engagement, leading to more effective learning outcomes.

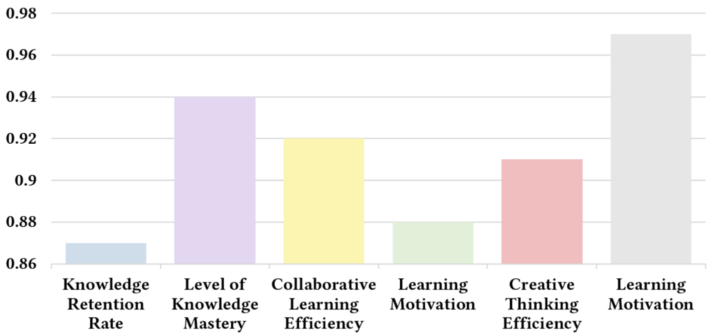

Fig. 1. The Impact of Using ChatGPT-4o with Pi and KG.

Based on these results, we recommend further exploration of the integration of Knowledge Graph (KG) and Personal Knowledge Proficiency (Pi) in educational technology applications. This approach not only improves students' knowledge retention and mastery but also significantly enhances collaborative learning efficiency and effectiveness, fostering more efficient problem-solving and thinking capabilities. Additionally, personalized learning support can bolster student motivation and engagement.

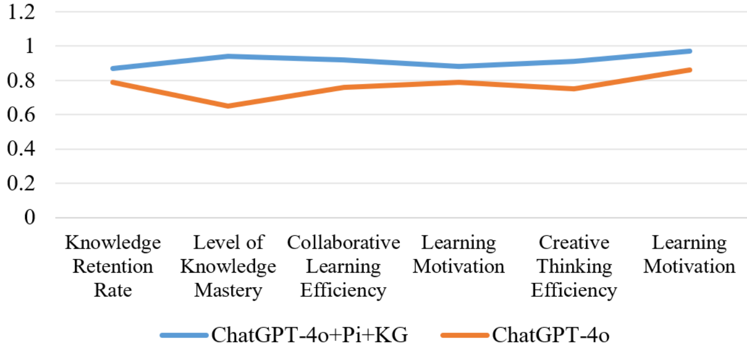

Fig. 2. Comparison Between ChatGPT-4o+Pi+KG and ChatGPT-4o.

In Figure 1 and Figure 2, the comparison between ChatGPT-4o (without Knowledge Graphs (KG) and Personal Knowledge Proficiency (Pi)) and ChatGPT-4o + Pi + KG (with KG and Pi) across various metrics illustrates the following key observations: The experimental group (ChatGPT-4o + Pi + KG) performed slightly better in terms of knowledge retention compared to the control group (ChatGPT-4o), indicating that the integration of KG and Pi supports long-term retention of information.

6 Conclusion

This research presents a novel exploration into the integration of Knowledge Graphs (KG) and students' knowledge mastery with LLM-generated text. Through a rigorous analysis of the interactions between the LLM, KG, Personal Knowledge Proficiency (Pi), context-specific Prompts (Pr), and knowledge (K), our study demonstrates that these integrations significantly advance Collaborative Problem-Solving skills.

Similarly, the work of Yu et al. (2024) on integrating social and knowledge graphs in GNN-based recommender systems highlights the powerful role of structured knowledge representations in improving system performance and personalization [2]. Their research aligns with our findings by showing how knowledge graphs can enhance the understanding of individual knowledge mastery and improve the effectiveness of recommendations. This supports the use of KGs in educational settings to tailor learning pathways and foster collaboration between students and AI, offering critical insights for future advancements in educational technology.

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