Kashihara, A. et al. (Eds.) (2024). Proceedings of the 32nd International Conference on Computers in Education. Asia-Pacific Society for Computers in Education

Scaffolding Students' Ill-Structured Problem Solving via LLM — Multi-Armed Bandit Problem as a Case

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Abstract: In this work, we explore the ability of LLMs to automatically generate hints for learners, taking the multi-armed bandit problem as a case. The ill-structured problem-solving process is divided into four stages: problem representation, solution generation, solution evaluation and adjustment, and final solution decision. We propose a prompt framework to fine-tune LLM based on four problem-solving stages and offer cognitive and metacognitive scaffolds at each stage. A preliminary study is conducted to analyze students' questioning tendencies and the quality of LLM-generated scaffolds. The results found that scaffolds generated by LLM were generally satisfactory, and effectively assisted learners in task analysis, domain knowledge supplementation, and solution iterations.

Keywords: ill-structured problems, large language model, human-AI collaboration

1. Introduction

Ill-structured problems are characterized by contextualization, connectivity between involved variables, dynamics of situation, intransparency, and multi-objectives (Funke, 2010). The scope of ill-structured problems is broad, this research takes the multi-armed bandit problem as a case. Multi-armed bandit problem has the features of contextualization, dynamics, and multi-objectivity, which align with the definition of ill-structured problems.

Solving ill-structured problems imposes high cognitive load and requires students to integrate multiple cognitive and metacognitive skills. However, current scaffolds proposed by researchers are mainly static scaffolds, presented as task sheets, which lack personalized guidance to assist students dynamically. This work aims to integrate problem-solving scaffolds into an LLM to automate scaffold generation, providing learners with cognitive and metacognitive support during problem-solving. Consequently, this research will develop an LLM-based ill-structured problem-solving platform and conduct preliminary experiments.

2. Methods

2.1 Prompt design based on problem-solving stages

The overall design of the prompt consists of system prompt and user prompt. System prompts deliver background information and ill-structured problem-solving scaffolding, while user prompts are primarily used for embedding problem descriptions and students' inquiries. This framework draws on previous research by scholars to divide the problem-solving process into different stages and offer guidance accordingly (Ge, 2004; Kim & Lim, 2019). First, we divide the problem-solving process into four stages: problem presentation, solution generation, solution evaluation and adjustment, and final solution decision. Then, we design a variety of learning scaffolds for each stage and point out the functions and goals of each scaffold to the

LLM. Finally, the prompt lists examples of questioning for each scaffold for the LLM to imitate for heuristic questioning.

We use GLM-4.0 to generate scaffolds for learners. The prompt framework is employed constantly during problem-solving. Each time, we prompt the model with backgrounds, scaffolds in four problem-solving stages, task description, and leaner query.

2.2 Preliminary Experiment Design

In this study, we designed a preliminary experiment to validate the effectiveness of scaffold generation by LLM. We designed four tasks with gradually increasing difficulty. The context of the task is that students, as entrepreneurs, need to conduct 10 collaborations with other companies. However, the payoffs of the candidates are unknown. Therefore, students need to balance their chances of exploration and exploitation, testing and selecting partners with high payoffs to maximize benefits within 10 collaborations. We developed a problem-solving platform as the experiment instrument, shown in Figure 1. The platform incorporates an LLM fine-tuned by the prompt based on problem-solving stages. It also provides a simulator to simulate partner payoffs, which assists students in calculating the benefits of different plans. The platform automatically collects the students' solutions and all dialogue data for analysis.

The participants in this experiment were 16 students majoring in Educational Technology or Computer Science. The participants were required to complete all tasks independently using our platform online within one hour. Participants were free to communicate with the LLM in Chinese but had no access to other online resources.

Data analysis mainly includes dialogue coding. We coded the students' queries and LLM responses according to four stages of problem-solving. We initially considered the LLM response effective if the LLM-generated scaffolds matched the stage of students' inquiries and were free of errors.

Figure 1. Main UI of LLM-based ill-structured problem-solving platform

3. Results

3.1 Students' questioning tendencies during ill-structured problem-solving

Finally, we received 59 solutions from 16 participants and collected 258 dialogue groups between LLM and students. The distribution of students' inquiries is shown in Figure 2. Most questions were asked during the solution generation stage, followed by the stage of solution evaluation and adjustment. Students mainly sought domain knowledge and iteration suggestions from LLM and seldom saw LLM as a cooperator. Besides, students rarely initiate a discussion like brainstorming with the LLM and tend to select final solutions alone.

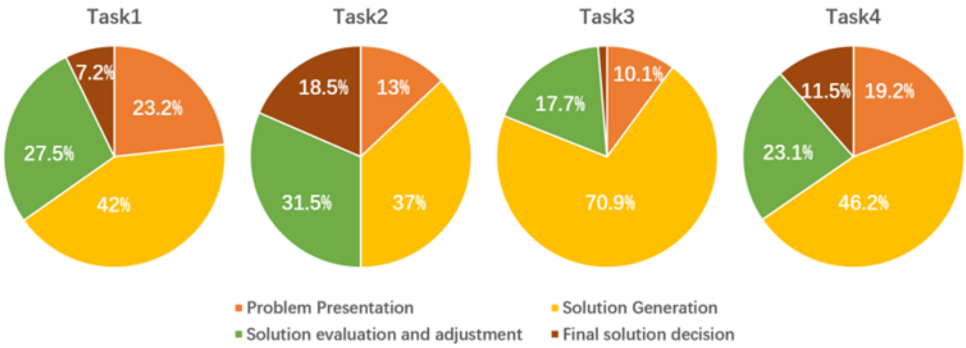

Figure 2. Percentage of Dialogue Number In Four Stages

3.2 The quality of hints generated by the LLM at each stage of problem-solving

We initially considered the LLM response effective if the generated scaffolds matched the stage of students' inquiries and had no error. The rate of effective LLM response during the four stages of problem-solving is shown in Table 1. The responses labeled as ineffective were mainly due to LLM's failure to recognize students' current stage of problem-solving.

Table 1. *Rate of effective LLM response during four stages of problem-solving*

Problem Presentation	Solution Generation	Solution evaluation and adjustment	Final solution decision
86.36%	57.97%	71.43%	90%

During the problem presentation stage, the hints generated by LLM successfully presented the objectives and variables of each task. During the solution generation stage, the LLM can explain related algorithms within the problem context. However, it had difficulty initiating brain-storming discussions, which required the student to give examples before further adding to the student's thinking. Besides, the LLM failed to further explain or build on previous questions when students failed to respond. During the stage of solution evaluation and adjustment, the LLM predominantly assessed the divergent thinking and adequacy of arguments in solutions instead of detecting errors. In the final solution decision stage, the LLM effectively assisted the students in abstracting the textual solutions into code.

4. Conclusions

This work shows LLMs' potential to generate hints for ill-structured problem-solving, taking the multi-armed bandit problem as a case. We propose a prompt framework to fine-tune LLM based on four problem-solving stages. A preliminary study was conducted to initially analyze students' questioning tendencies and the quality of LLM-generated scaffolds. The prompt design based on the four problem-solving stages can be applied to train LLMs in other ill-structured problem contexts.

References

Funke, J. (2010). Complex problem solving: A case for complex cognition?. Cognitive processing, 11, 133-142.

Ge, X., & SM, L.(2004). A conceptual framework for scaffolding III-structured problem-solving processes using question prompts and peer interactions. Educational technology research and development, 52(2), 5-22.

Kim, J. Y., & Lim, K. Y. (2019). Promoting learning in online, ill-structured problem solving: The effects of scaffolding type and metacognition level. Computers & Education, 138, 116-129.