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User Learning Behaviors in Knowledge-Enhanced Large Language Models

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Abstract: This study examines differences in user learning interaction behaviors based on knowledge-enhanced large language models (LLMs). It explores the impact of digital literacy and cognitive learning models on user interaction methods. By constructing a systematic framework for analyzing learning interactions, this study integrates in-depth interviews, experimental research, and statistical analysis to reveal significant behavioral variations in knowledge acquisition, problem-solving, and information reconstruction. Experimental results indicate that users with low digital literacy tend to increase query frequency and adjust search strategies to compensate for limitations in information processing. In contrast, users with higher digital literacy demonstrate stronger expression adjustments and enhanced knowledge integration. Additionally, cognitive learning models significantly shape interaction patterns. Evaluative learners engage in more in-depth conversations and intensive reading, while receptive learners rely on the model's direct outputs and rarely reconstruct information. The findings deepen the understanding of user learning behaviors in knowledge-enhanced LLMs. They also provide a theoretical foundation for optimizing personalized learning support and intelligent interaction design. Future research will explore more complex interaction factors and incorporate personalized user characteristics to enhance the effectiveness of large language models in intelligent learning environments.

Keywords: Knowledge-enhanced large language model, learning interaction behavior, digital literacy, cognitive learning model

1. Introduction

Artificial intelligence-generated content (AIGC) has become a key research area in intelligent interaction and user information behavior. With the rapid advancement of large language models, their applications in education, scientific research, and enterprise management have expanded significantly[1]. Compared to traditional information retrieval and knowledge acquisition methods, knowledge-enhanced large language models provide users with more accurate and structured knowledge by integrating external knowledge bases and enhancing reasoning capabilities. However, most research focuses on macro-level aspects, such as AIGC's technological progress, application scenarios, and societal impact. Few studies explore how users interact with knowledge-enhanced large language models during learning, optimize learning behaviors, or examine the cognitive and emotional characteristics behind these interactions from a micro perspective[2]. Investigating differences in user learning interaction behaviors with knowledge-enhanced large language models will deepen theoretical exploration in intelligent learning and contribute to personalized learning environments[3].

As one of the most representative knowledge-enhanced large language models, ChatGPT demonstrates strong capabilities in intelligent interaction, knowledge integration, and problem-solving. Its applications in learning and education are steadily increasing. However, user behavior when using ChatGPT for learning varies significantly. Some users engage in exploratory learning through continuous and in-depth conversations, while others prefer direct answers. Some efficiently integrate model-generated knowledge into systematic cognition, while others remain at a superficial level of information acceptance. Emotional experiences, such as trust, anxiety, and cognitive load, also influence user learning behaviors. Analyzing these learning interaction differences from cognitive, behavioral, and emotional dimensions is crucial for optimizing the learning support functions of knowledge-enhanced large language models and enhancing user learning experiences[4].

This study systematically analyzes differences in user learning interaction behaviors with knowledge-enhanced large language models and explores key influencing factors. First, it reviews relevant domestic and international literature to clarify the role of these models in intelligent learning and develops a systematic framework for analyzing learning interactions. Next, through in-depth interviews and grounded theory, the study examines user interaction patterns and explores the influence of cognitive characteristics, emotional experiences, and other factors on learning behaviors. Additionally, experimental research and statistical analysis are used to assess the impact of digital literacy and cognitive learning models on user learning behaviors and their interactions in the learning process. The findings will enhance the understanding of how knowledge-enhanced large language models facilitate user learning and provide a scientific basis for optimizing their application in education.

As knowledge-enhanced large language models continue to evolve, their value in intelligent learning environments becomes increasingly evident. However, user learning behaviors during interactions with models like ChatGPT remain complex and diverse. These behaviors are influenced not only by cognitive styles and digital literacy but also by learning contexts and interaction methods. This study provides a micro-level analysis of user learning interactions with knowledge-enhanced large language models, offering new insights into AIGC-driven intelligent learning. The findings will support the optimization of intelligent interactive experiences and personalized learning environments. They will also enhance the effectiveness of large language models in education and provide theoretical and empirical support for the future development of AIGC technology and intelligent education systems[6].

2. Related Work on Learning Interactions in Knowledge-Enhanced LLMs

Researchers have extensively discussed the role of large language models in various learning scenarios. Some studies focus on their knowledge generation and retrieval capabilities. They suggest that the knowledge enhancement mechanism effectively compensates for traditional neural networks' weaknesses in factual reasoning and long-term memory. As a result, users gain more accurate and reliable learning support. Other scholars analyze the performance of knowledge-enhanced large language models from the perspective of learning adaptability. They highlight significant differences in applicability based on users' cognitive levels. For example, users with high cognitive abilities leverage the model's reasoning capabilities for deep learning. In contrast, users with lower cognitive abilities may experience information overload or cognitive bias. Optimizing the learning interaction mechanism of knowledge-enhanced large language models to better suit diverse user needs remains a key research focus[7].

Beyond knowledge acquisition and learning adaptability, user learning interaction behavior has also gained attention in recent years. Studies show that interactions with large language models are influenced by both model-generated content and individual factors such as learning style, goal orientation, and trust in artificial intelligence. For example, research indicates that users adopt different learning strategies, including exploratory interaction, critical questioning, and linear knowledge retrieval. These strategies significantly impact learning outcomes. Additionally, some scholars examine cognitive load and emotional experiences in learning. They argue that when users encounter complex tasks or information uncertainty, cognitive load

increases, reducing interaction efficiency and learning effectiveness. Therefore, understanding how users optimize learning interactions and balance cognitive load with learning benefits is essential for enhancing the practical application of these models[8].

Digital literacy and personalized learning models also play a crucial role in shaping user interactions with knowledge-enhanced large language models. Researchers note that users with higher digital literacy efficiently use models to build knowledge. In contrast, those with lower digital literacy tend to rely on intuitive answers without deeper understanding or critical thinking. Additionally, cognitive learning models influence interaction styles. Receptive learners prefer clear conclusions, while creative learners engage in divergent thinking exploration. Optimizing learning interaction design to accommodate different user types has become a critical topic in intelligent learning research. Building on previous work, this study will further examine the learning interaction patterns of different user groups and propose optimization strategies to enhance applicability and user experience in intelligent learning scenarios.

3. Modeling Framework and Analytical Methodology

This study aims to construct a theoretical framework for the learning interaction behavior of knowledge-enhanced large language models and explore the impact of digital literacy and cognitive learning models on learning interaction behavior. To this end, we adopted a multi-level modeling approach, combined with qualitative analysis and quantitative experiments, to systematically explore the differences in learning behavior and their potential mechanisms among different user groups when interacting with knowledge-enhanced large language models[9]. The study first extracted the key factors that affect learning interaction behavior based on in-depth interviews and grounded theory, and constructed a theoretical framework for learning interaction behavior; then, based on experimental research and statistical analysis, a mathematical model of learning interaction behavior was established to quantify the impact of different factors on interaction patterns. The overall framework is shown in Figure 1.

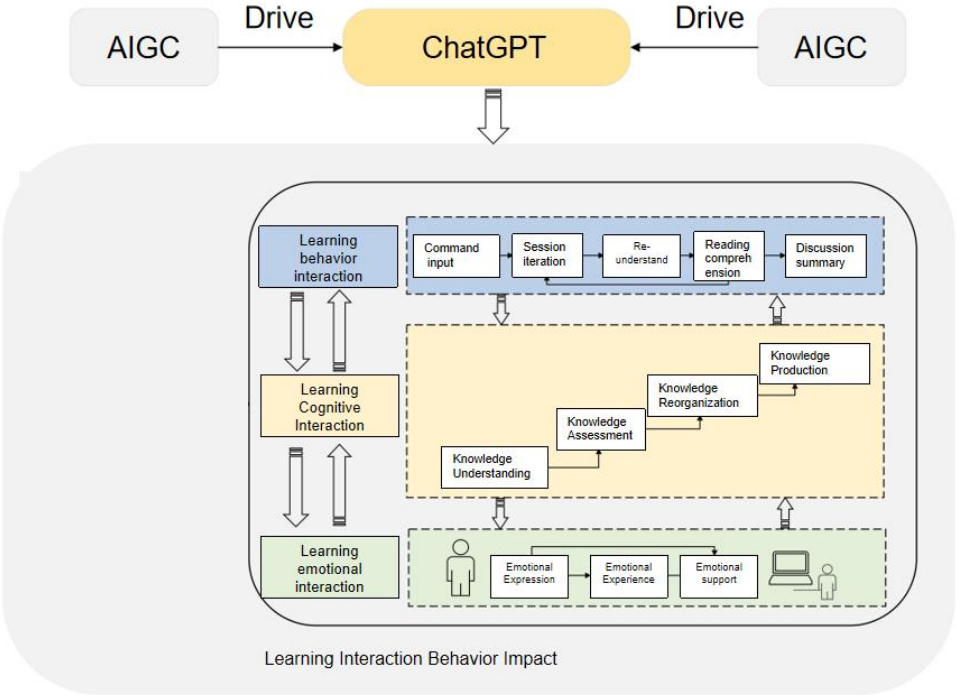


Figure 1. Overall framework

Assume that the learning interaction behavior of the knowledge-enhanced large language model user can be represented as a multidimensional vector $X = (x_1, x_2, ..., x_n)$, where each x_i represents a specific interaction

behavior variable, such as information query frequency, question depth, cognitive load level, etc. We define the user's learning effect Y as a function of learning interaction behavior:

$$Y = f(X, D, C) + \varepsilon$$

Among them, D represents the user's digital literacy level, C represents the user's cognitive learning model, and ε is the error term. In order to explore the main effect and interaction of digital literacy and cognitive learning model on learning interaction behavior, we use a linear regression model:

$$Y = \beta_0 + \beta_1 D + \beta_2 C + \beta_3 DC + \sum_{i=1}^{n} \beta_i x_i + \varepsilon$$

Among them, β_3 represents the interaction coefficient between digital literacy and cognitive learning mode. If it is significant, it means that there is an interaction between the two in the learning interaction behavior.

In addition, in order to further explore the specific mode of user learning behavior interaction, we introduce the human-computer dialogue round T as an indicator to measure the depth of user interaction. Based on the user's learning cognitive model C and digital literacy D, we assume that the human-computer dialogue round conforms to the Poisson distribution:

$$P(T = k) = \frac{\lambda^k e^{-\lambda}}{k!}$$

Among them, λ is the expected value of the dialogue round, which can be calculated by the following formula:

$$\lambda = a_0 + a_1 D + a_2 C + a_3 DC$$

When a_3 is significant, it indicates that there is an interactive effect between digital literacy and cognitive learning mode on the number of human-computer dialogue turns. Furthermore, we use a negative binomial regression model to correct the overdispersion problem of the Poisson distribution and verify the significant differences in the number of human-computer dialogue turns among different user groups.

In the learning interaction process, the user's cognitive load L is also an important factor affecting learning outcomes. We use cognitive load theory (CLT) to decompose the total cognitive load L into intrinsic cognitive load L_I, extrinsic cognitive load L_E and essential cognitive load L_G.

Among them, L_I is determined by the complexity of the learning task itself, L_G depends on the user's knowledge level, and L_E is affected by the learning interaction method. We assume that L_E is a function of the learning interaction variable X:

$$L_E = \gamma_0 + \sum_{i=1}^{n} \gamma_i x_i + \delta$$

Among them, δ is the error term. Through structural equation modeling (SEM), we further verify how learning interaction behavior affects cognitive load and explore its indirect effect on the final learning effect Y.

In summary, this study systematically explores the patterns and influencing factors of user learning interaction behaviors of knowledge-enhanced large language models through theoretical modeling, regression analysis, Poisson/negative binomial regression, and structural equation modeling. Experimental data will be collected through actual user testing and online experiments, and verified using multivariate statistical analysis methods. This study not only provides a mathematical foundation for theoretical exploration in the

field of intelligent learning, but also provides a scientific basis for optimizing the learning interaction design of knowledge-enhanced large language models.

4. Experimental Design and Data Collection

4.1 Datasets and User Grouping

The dataset used in this study is derived from the learning interaction behavior data of real users, covering detailed records of users with different backgrounds and digital literacy levels interacting with the knowledge-enhanced large language model. Data collection uses a combination of online experiments and log records to invite users to interact with the large language model under specific learning tasks, and automatically records key information such as user input, system feedback, interaction time, and human-computer dialogue rounds during this process. In addition, in order to deeply analyze the user's learning cognitive model and emotional experience, the study also collects users' subjective feedback through questionnaires and in-depth interviews, including variables such as learning goals, trust in the model, and cognitive load perception, so as to construct a more comprehensive dataset.

The dataset contains information at multiple levels, including basic user characteristics, interaction behavior data, and subjective feedback data. The basic user characteristics include age, educational background, professional field, and digital literacy level, so as to analyze the behavioral differences of different user groups in learning interactions. The interaction behavior data mainly records the user's learning methods in the model, such as query type, number of interactions, information depth, and learning task completion. These data will be used to analyze the learning interaction behavior pattern. Subjective feedback data is evaluated in the form of a Likert scale to evaluate the user's emotional experience, learning load, and satisfaction with the model-generated content during the learning process, in order to explore the impact of user cognitive and emotional factors on learning behavior. In addition, in order to improve the reliability and generalization of the data, the data collection process strictly follows the experimental control principle to ensure that different user groups interact under the same task conditions, and to clean and preprocess abnormal data.

The quality control of the data set uses a variety of methods, including removing duplicate samples, cleaning invalid inputs, standardizing the interaction log format, and using data visualization technology to analyze data distribution and trends. In addition, this study uses a two-person verification mechanism in the data annotation process to ensure the accuracy of the subjective feedback data, and balances the data set to reduce the impact of sample bias. The final data set can be used to quantitatively analyze the learning interaction behavior of different user groups, provide empirical evidence for exploring the learning support function of the knowledge-enhanced large language model, and can also be used for interaction optimization and model improvement in subsequent research.

4.2 Task Construction and Interaction Recording

The experimental task design used in this paper is shown in Table 1.

Table 1: Experimental design

Task	**Specific tasks**
Task1	If you love traveling and want to go to Iceland to watch a volcanic eruption, you want to know why this phenomenon occurs in Iceland, what month you can see volcanoes in Iceland, and what other precautions you should pay attention to before you plan to go. Please search for relevant information on ChatGPT and record your answers in a word document during the search process.

Task2	Recently, we have entered the season change stage. Due to the large temperature difference between morning and evening and the dry weather, your cousin who is in high school has relapsed with seasonal rhinitis. Due to his busy studies, his cousin cannot go to the hospital for treatment in time. Can you help him solve the following problems: What traditional or modern methods can be used to treat rhinitis? How effective are the drugs? Which method do you think is the best? Why? Please search for relevant information on ChatGPT and record your answers in a word document during the search process.
Task3	Suppose you are a writer for an online magazine. Recently, the editorial department wants you to write a short article on the theme of "Smart speakers - companions in daily life". You are asked to use ChatGPT to search, collect useful information during the search process, and complete the writing of the short article (no less than 500 words).

The experimental process includes four parts: first, users complete the digital literacy measurement questionnaire; second, in order to facilitate the researchers to conduct statistical analysis of the data generated during the experiment, it is recommended that the subjects use "ChatGPT" (web version) to complete the three tasks set in the experiment. At the beginning of the experimental task, use EV Capture software to record the screen. During the information query process, useful information can be recorded in a Word document at any time. When the subject thinks that he has found the answer to the task, the query is completed and the screen recording can be ended; third, each time a task is completed, fill in the emotional experience measurement questionnaire once, and complete three tasks and three emotional experience measurement questionnaires in total; fourth, organize the answers to the query in a Word document and send it to the researcher's email together with the screen recording video.

4.3 Measurement Indicators and Variable Definitions

Therefore, through the design of the above experiments, this paper can obtain relevant experimental results, and the experimental results are shown in Table 2.

Table 2: Experimental results

Learning behavior interaction	**Digital Literacy**	**Cognitive Learning Model**	**Digital literacy × cognitive learning model**
Query Quantity	7.274	6.944	5.905
Human-computer dialogue rounds	8.488	8.389	8.760
Number of rephrased statements	2.083	2.456	1.625
Number of times new query terms were introduced	3.844	2.845	2.289
Intensive reading times	9.167	8.567	8.367

The experimental results show that digital literacy and cognitive learning mode have a certain impact on users' learning interaction behavior, but the degree of influence of different variables varies. First, in terms of the number of queries, low digital literacy users (7.274) have a slightly higher number of queries than high digital literacy users (6.944), while receptive learners (5.905) have the lowest number of queries, indicating that cognitive learning mode may affect users' query tendencies to a certain extent. Second, in terms of the

number of human-computer dialogue turns, evaluative learners (8.760) are higher, while creative learners are lower (not listed), which may mean that evaluative learners tend to have more in-depth dialogues during the interaction process. In terms of the number of rephrasing sentences, users with higher digital literacy (2.456) are more inclined to adjust their expressions than users with lower digital literacy (2.083), while receptive learners (1.625) are less likely to reconstruct, indicating that they may rely more on the direct output of the model during the interaction process. The number of times new query terms were introduced showed that low digital literacy users (3.844) were more inclined to try new query methods than high digital literacy users (2.845), which may reflect their need to constantly adjust strategies in the process of information acquisition. Finally, in terms of the number of intensive readings, low digital literacy users (9.167) and evaluative learners (8.367) had higher numbers of intensive readings, which may indicate that these users rely more on detailed reading in information processing to compensate for cognitive uncertainty.

Overall, users with low digital literacy are more inclined to compensate for the lack of information processing ability by increasing the number of queries and adjusting search strategies during learning interactions, while cognitive learning modes affect users' interaction depth and information reconstruction methods. These results provide important empirical evidence for optimizing the personalized learning interaction design of knowledge-enhanced large language models.

Finally, this paper also conducted time pressure and cognitive load experiments, and the experimental results are shown in Figure 2.

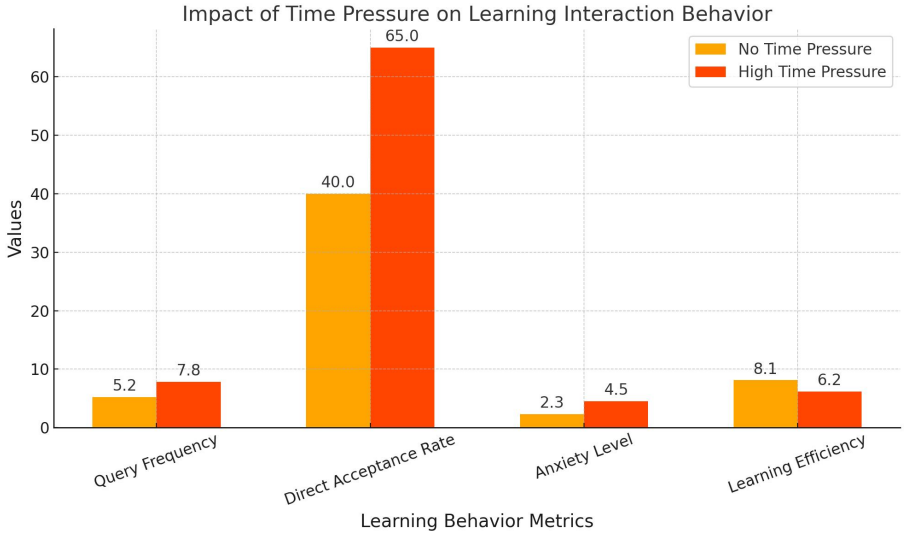


Figure 2. Time pressure and cognitive load experiment

The experimental results indicate that time pressure significantly impacts user interaction behavior with large language models. Under high time pressure, users tend to increase their query frequency (7.8 vs. 5.2) as they attempt to retrieve information more quickly. Additionally, they exhibit a higher direct acceptance rate of LLM-generated responses (65% vs. 40%), suggesting that users under pressure are less likely to critically evaluate or reconstruct information, instead opting for immediate answers. This behavior implies that time constraints push users to adopt a more surface-level approach to information processing, prioritizing efficiency over depth.

Moreover, the results show that cognitive load and emotional response are also affected by time pressure. Users in the high-pressure condition report significantly higher anxiety levels (4.5 vs. 2.3), which could negatively impact their decision-making and learning effectiveness. Correspondingly, their overall learning efficiency decreases (6.2 vs. 8.1), indicating that while time pressure may accelerate information retrieval, it does not necessarily enhance comprehension or retention. These findings suggest that optimizing LLM

responses under time constraints-such as providing structured summaries or key insights-could help mitigate cognitive overload and improve user learning outcomes in high-pressure scenarios.

5. Conclusion

This study explored the differences in learning interaction behaviors among users of the knowledge-enhanced large language model, focusing on the impact of digital literacy and cognitive learning models on learning interaction behaviors. The experimental results show that users with low digital literacy tend to increase the number of queries and adjust search strategies during the learning process to make up for the lack of information processing ability, while users with higher digital literacy show stronger expression adjustment and knowledge integration capabilities during the interaction process. In addition, cognitive learning models play an important role in influencing the user interaction mode. Evaluative learners tend to have in-depth conversations and intensive reading, while receptive learners rely more on the direct output of the model and rarely reconstruct information. These findings not only deepen the understanding of user learning behavior patterns, but also provide a reference for the design of personalized learning support for knowledge-enhanced large language models. The conclusions of this study can provide a theoretical basis for the optimization of intelligent learning systems. Future research can further explore more complex interaction factors and combine user personalized characteristics to improve the application effect of large language models in the field of learning.

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