Assessing The Impact of Enhancing AI-Driven Educational Applications Using Emotional Blackmail Prompts in Large Language Models

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***Abstract*—The rapid integration of Artificial Intelligence (AI) in educational systems has revolutionized teaching and learning methodologies, mainly through the advancement of Generative AI (GAI). This study evaluates the efficacy of emotional blackmail prompts—a novel interaction strategy designed to enhance the responsiveness of large language models (LLMs) like GPT4o, Kimi, and Gemini in educational applications. By leveraging a methodological framework that combines bibliometric and text analysis, our research reveals significant variations in how these models process and respond to emotionally charged prompts. The findings suggest that emotional blackmail can influence the quality and accuracy of AI-generated educational content, highlighting GPT4o's superior ability to adapt to emotional cues compared to other models. This study sheds light on the potential of emotional blackmail prompts to refine AI interactions. It also discusses such strategies' ethical implications and practical applications in improving AI-driven educational tools.**

Keywords—AI-Driven Education, Emotional Blackmail, Bibliometric Analysis, Text Analysis, Large Language Model

I. INTRODUCTION

In 21st-century education, integrating Artificial Intelligence (AI) technology is progressively transforming traditional teaching and learning paradigms. Research indicates that AI has immense potential in personalized learning, intelligent assessment, and content generation. Concurrently, the rapid development of Generative AI (GAI) has significantly impacted academic writing, with students leveraging GAI to enhance their performance in writing tasks [1]. Furthermore, the swift advancement of GAI has also improved reading and writing efficiency [2], particularly in drafting titles and designing thesis outlines, where AI can provide substantial assistance to scholars [3]. However, AI still falls short in assisting with reading, such as failing to grasp accurate information or producing erroneous outputs [4]. Therefore, how to make AI more precisely understand and respond to users' inquiries and needs in the field of education is an urgent issue to be addressed.

This study explores innovative methods to enhance the quality of responses from local language models and generative AI in educational contexts. Among these methods, the emotional blackmail questioning approach, as a new interaction strategy, has shown potential in educational AI applications due to its keen perception of emotions and context through an in-depth evaluation of the emotional blackmail questioning approach to investigate its effectiveness in improving the quality of AI-generated educational content, thereby providing new perspectives and insights for future intelligent education.

II. LITERATURE REVIEW

A. *The Application of Artificial Intelligence in Education*

Integrating AI into the educational sector has profound implications for teaching, learning, and administration. AI is utilized to optimize educational development, foster synergy between intelligent technologies and the education industry [5], enhance efficiency, personalize learning experiences, and streamline tasks[6]. Moreover, AI is also being utilized for predictive modeling, intelligent analytics, assistive technologies, automatic content analysis, and image analytics, addressing critical education issues and contributing to the quality of education [7]. The application of AI in education encompasses machine learning, knowledge mapping, natural language processing, robotics, and intelligent control, including emerging technologies such as virtual reality, big data, and 5G [8].

B. *The Impact of GAI on Academic Writing*

AI plays a pivotal role in enhancing writing capabilities today. Students who engage in iterative and highly interactive processes with GAI-powered tools typically perform better academic writing tasks [1]. Large Language Models, such as ChatGPT, elevate the quality of texts and recast writing as a collaborative process [9]. These AI tools serve as automated writing assessment tools, offering more stringent grading criteria than human evaluators, targeted feedback on higher-level writing elements, and supporting multiple submissions, enhancing learner autonomy [10]. Generative AI functions as a virtual assistant, providing support throughout the writing process and complementing students' knowledge and skills without supplanting them [11]. However, this potential enhancement has also led to scholars raising concerns about originality and the risk of plagiarism [12].

C. *The Impact of emotional blackmail prompts on AI Educational Applications*

Emotional blackmail is a form of repetitive emotional manipulation involving threats to hurt or abandon a person close to the perpetrator, inducing fear, obligation, or guilt [13]. Although AI can understand and analyze some human emotions [14], challenges remain in accurately interpreting human emotions and ethical considerations [15].

While AI-powered question-and-answering bots are highlighted as promising tools for providing immediate support and personalized learning experiences, concerns about the accuracy of assistive reading are acknowledged as a challenge that requires careful attention and management [16]. The accuracy of the information output of AI applications in education is a crucial issue, with possible reasons including (1) inadequate training and support, limited access to technology, and infrastructure issues [17]; (2) an incomplete algorithm design and insufficient labeled data, which are identified as issues [18]; and (3) AI models are a significant concern, hindering the understanding of their decision-making processes and establishing trust in their outcomes [19].

III. Experimental Design and Research Methods

Taking the Scopus platform as an example, this study employed a literature search method targeting documents with keywords related to AI and Education. The search results revealed over 2600 documents from 1984 to 2024. A bibliometric analysis was conducted on these documents using the VOSviewer software, and the resulting visualization is depicted in Figure 1.

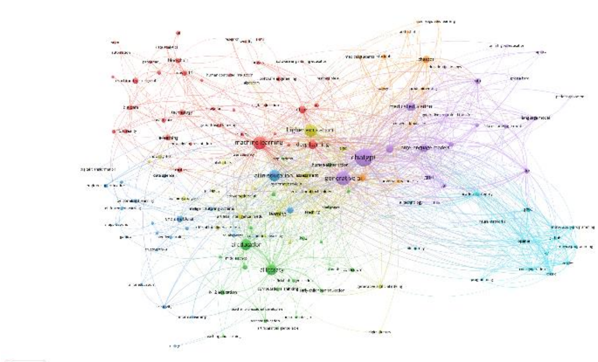

Fig. 1. *bibliometric analysis map*

The visualization map was divided into five main areas, with an additional search term selected from each:

- Red Zone: Focusing on technical aspects of AI, the additional search term is "machine learning."
- Blue Zone: Exploring AI's theoretical and practical applications in education, the additional search term is "AI in education."
- Yellow Zone: This zone focuses on integrating AI with education in higher education settings, so the additional search term is "higher education."
- Purple Zone: Discussing the application of language models in education, the additional search term is "generative AI."
- Green Zone: Investigating the teacher-student relationship and the role of AI in education across different age groups, the additional search term is "AI literacy."

This study leveraged Scopus to identify the five most-cited documents per keyword, compiling 25 articles for analysis. Employing the Breeze model in LM Studio and three cloud-based models—GPT4o, Gemini, and Kimi—the pilot study assessed AI's capability to summarize core content under structured reading and emotionally influenced summarization. Comparative text analysis was utilized to evaluate the AI-generated summaries.

IV. Text Analysis

A. *Paper analyze*

In this study, the abstracts, discussions, and conclusions of the selected 25 articles were extracted, subjected to text cleaning, and analyzed using KH CODER software. Corresponding co-occurrence network diagrams and correspondence analysis maps were generated (Figures 2 and 3).

The co-occurrence network diagram reveals that among the 25 articles selected for this study, two cluster topics exhibit a high frequency of co-occurrence. A higher co-occurrence frequency suggests that these topics are semantically closely related and form a conceptual group. For instance:

1) In Subgraph 5, terms such as "student," "education," "study," "teacher," "learn," and "research" are more frequently used than other words. This suggests that this subgraph primarily discusses issues related to teacher-student interactions and the impact of technology on teaching.

2) In Subgraph 3, terms like "information," "academic," "ChatGPT," and "skill" have a higher co-occurrence frequency than other words. This indicates that this subgraph mainly addresses the influence of these AI tools on teaching and the enhancement of writing skills.

3) Other subgraphs also reveal terms with high co-occurrence frequencies. For instance, in Subgraph 6, terms such as "improve," "development," and "application" are prominent, indicating that this subgraph focuses on topics related to product development, improvement, and application. Similarly, in Subgraph 4, terms like "issue," "theory," and "learner" are prominent, suggesting that this subgraph primarily discusses theories related to student learning.

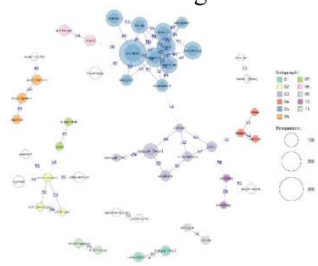

Fig. 2. 25 paper's co-occurrence network diagrams

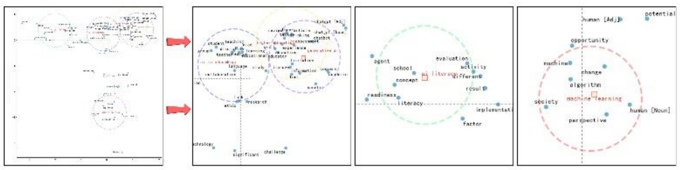

Fig. 3. 25 paper's correspondence analysis maps

The red squares in the correspondence analysis map represent keywords extracted from the selected articles. The map shows that the topics of "AI in education," "AI literacy," "generative AI," and "higher education" are distributed along the X-axis, indicating a certain degree of correlation among these topics. "Machine learning," however, is situated farther away, suggesting a weaker correlation. Among these, "higher education" and "generative AI" are the most closely related in content. A summary of the most similar terms for each topic is presented in Table 1.

TABLE I. MOST SIMILAR TERMS FOR EACH TOPIC

	ai literacy	ai in education	higher education	generative ai	machine learning
Word 1	school	language	experience	limitation	algorithm
Word 2	concept	collaboration	assseement	improve	perspective
Word 3	literacy	teacher	thinking	information	change
Word 4	evaluation	discipline	skill	tool	human
Word 5	activity	learn	education	chatbot	society

B. Test of local language model(LLM)

The testing of the local language model utilized the Breeze language model within LM Studio. Because the local language model cannot read documents directly, it analyzed the abstracts, discussions, and conclusions of the 25 articles after text cleaning. After reading, the local language model was tasked with summarizing the core content of each article. After text cleansing, summarization, and analysis of the responses generated by the local language model, this study created co-occurrence network diagrams and correspondence analysis maps under different scenarios: the co-occurrence network (Figure 4), the co-occurrence network after emotional blackmail (Figure 5), and the correspondence analysis map with or without emotional blackmail prompts (Figure 6).

Figure 4 indicates that the local language model yielded higher co-occurrence frequencies for terms such as "Education," "learn," "student," and "ChatGPT." However, in the emotional blackmail scenario (Figure 5), the co-occurrence of these key terms decreased.

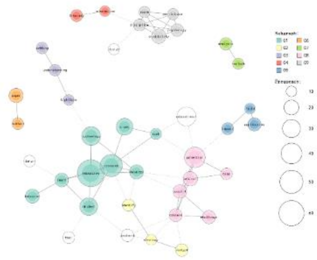

Fig. 4. LLM co-occurrence network diagrams

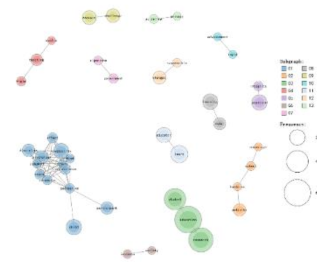

Fig. 5. LLM co-occurrence network after emotional blackmail

Figure 6 shows that the local language model perceived a certain degree of correlation between "AI literacy", "higher education", "generative AI", and "machine learning", but the topic "AI in education" was notably distinct. Only some near "generative AI" were correctly identified in capturing keywords related to these topics. After emotional blackmail prompts, the model recognized correlations among "higher education," "generative AI," and "machine learning." Except for "AI in education," keywords near the other four topics were correctly captured.

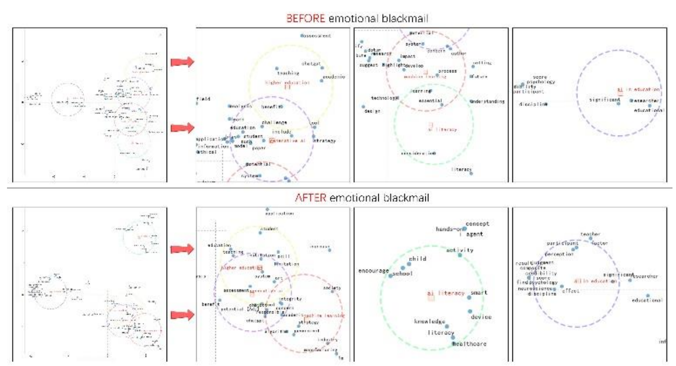

Fig. 6. LLM correspondence analysis map with or without emotional blackmail prompts

C. Test of Kimi

One of the large language model tests utilized an artificial intelligence developed by Moonshot AI, a company based in Mainland China. Kimi AI read the full text of 25 papers and needed to summarize the core content. After text cleansing, summarization, and analysis of the responses generated by Kimi AI, this study created co-occurrence network diagrams and correspondence analysis maps under different scenarios: the co-occurrence network (Figure 7), the co-occurrence network after emotional blackmail (Figure 8), and the correspondence analysis map with or without emotional blackmail prompts (Figure 9).

Figures 7 and 8 indicate that the co-occurrence frequency of Kimi AI's core keywords was relatively low, regardless of emotional blackmail.

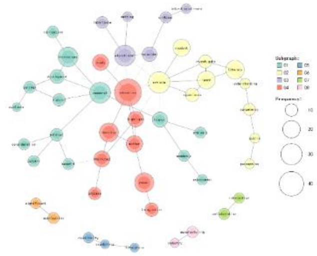

Fig. 7. Kimi co-occurrence network diagrams

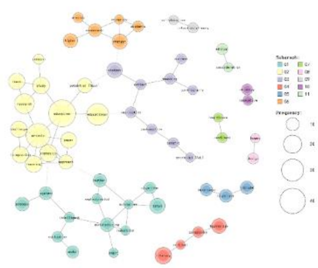

Fig. 8. Kimi co-occurrence network diagrams after emotional blackmail

Figures 9 show that Kimi AI showed high correlations between the topics of "AI in education," "higher education," "generative AI," and "machine learning," with or without emotional blackmail. Notably, Kimi AI captured one or two key terms near each topic. However, there was no significant change in the number and proximity of these key terms, irrespective of the use of emotional blackmail.

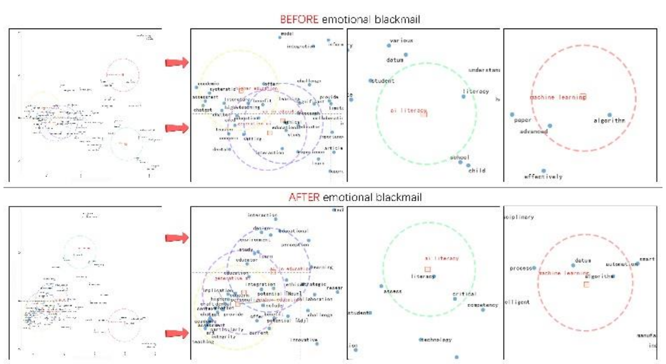

Fig. 9. Kimi correspondence analysis map with or without emotional blackmail prompts

D. Test of Gemini

One of the large language model tests utilized an artificial intelligence developed by Google, known as Gemini. Gemini AI read the full text of 25 papers and needed to summarize the core content. After text cleansing, summarization, and analysis of the responses generated by Gemini AI, this study created co-occurrence network diagrams and correspondence analysis maps under different scenarios: the co-occurrence network (Figure 10), the co-occurrence network after emotional blackmail (Figure 11), and the correspondence analysis map with or without emotional blackmail prompts (Figure 12).

Figure 10 shows that within subgraph 3, terms such as "education," "technology," and "research" have a higher co-occurrence frequency compared to other terms, consistent with the original text. However, Figure 11, after emotional blackmail prompts, displays additional high-frequency co-occurring terms, such as "ChatGPT" and "information" in Subgraph 1 and "outcome" in Subgraph 13.

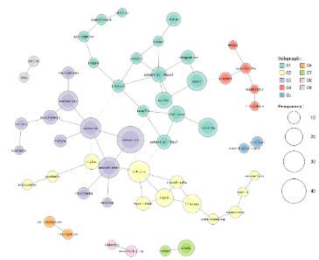

Fig. 10. Gemini co-occurrence network diagrams

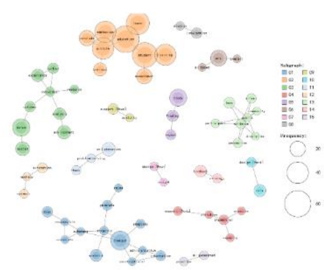

Fig. 11. Gemini co-occurrence network diagrams after emotional blackmail

Figure 12 indicates that Gemini identifies a strong correlation between the topics of "generative AI" and "AI in education," with keywords identified related to the subjects of "higher education," "machine learning," and "AI literacy." After emotional blackmail prompts, Gemini continues to identify a connection between "higher education" and "AI in education," but there is no significant change in the identified keywords.

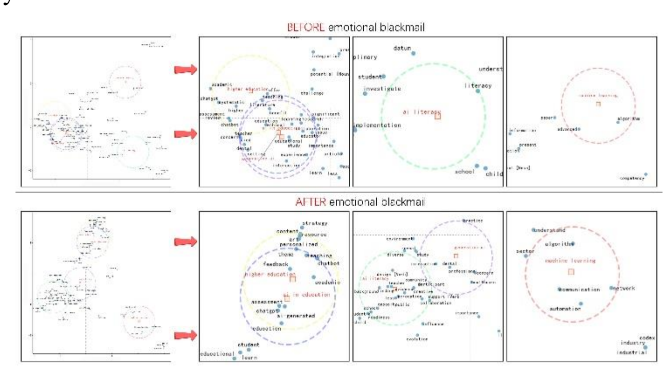

Fig. 12. Gemini AI correspondence analysis map with or without emotional blackmail prompts

E. Test of ChatGPT4o

One of the large language model tests utilized an artificial intelligence developed by OpenAI, known as ChatGPT4o. ChatGPT4o read the full text of 25 papers and needed to summarize the core content. After text cleansing, summarization, and analysis of the responses generated by ChatGPT4o , this study created co-occurrence network diagrams and correspondence analysis maps under different scenarios: the co-occurrence network (Figure 13), the co-occurrence network after emotional blackmail (Figure 14), and the correspondence analysis map with or without emotional blackmail prompts (Figure 15).

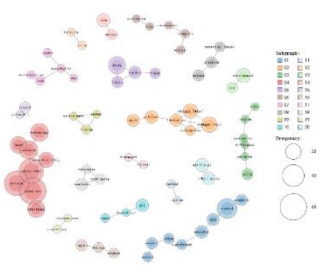

Fig. 13. ChatGPT4o co-occurrence network diagrams

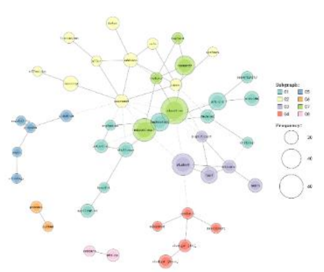

Fig. 14. ChatGPT4o co-occurrence network diagrams after emotional blackmail

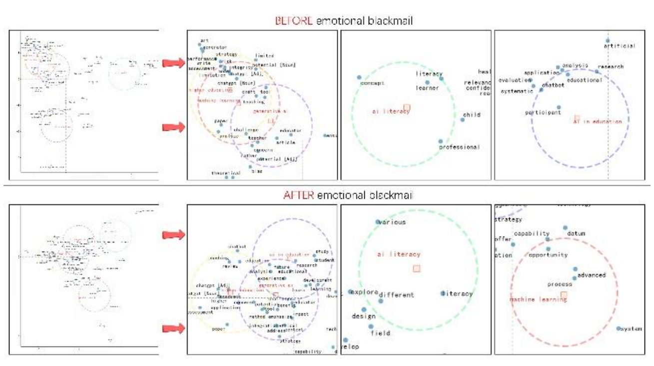

Fig. 15. ChatGPT4o correspondence analysis map

Figure 13 illustrates the capture of several correct high-frequency co-occurring terms, such as "student" and "academic" within subgraph 1, "ChatGPT" and "skill" within subgraph 2, and "education," "technology," and "research" within subgraph 4. In this pilot study's scenario, ChatGPT4o captured more high-frequency co-occurring terms than the local language model, Kimi AI, and Gemini. After emotional blackmail prompts (Figure 14), ChatGPT4o identified an even broader spectrum of high-frequency terms dispersed across various subgraphs; for instance, "academic," "ChatGPT," "advanced," and "assessment" in subgraph 4 are recognized as a cluster of frequently co-occurring terms. Additionally, the diagram indicates that GPT4o, in this context, outmatched other AIs in identifying terms closely related to the original text's intent.

Figure 15 demonstrates that the subjects of "higher education," "machine learning," and "generative AI" exhibit closer affinity, yet only a single correct keyword was identified in their vicinity; these accurate keywords, however, were found proximal to the topics of "AI in education" and "AI literacy." Regrettably, only two keywords were accurately identified near the latter two subjects. After emotional blackmail prompts , no correct keywords were found near "machine learning," while two to three accurate keywords were identified near the other four topics.

V. Discussion and Conclusions

Our bibliometric and text analysis findings offer significant insights into how emotional blackmail prompts affect the performance of large language models (LLMs) in educational applications. Our comparative study across models like GPT4o, Kimi, and Gemini demonstrates varying proficiency in interpreting and responding to emotional cues embedded within educational content.

Kimi and Gemini were less affected by the emotional blackmail questioning method, and there were no significant changes in the associations between the topics and keywords captured in their responses based on their responses, regardless of whether or not they were asked using this method.

The GPT4o model's performance under the emotional blackmail questioning method was particularly striking, as evidenced by its precise topic capture abilities (refer to Figure 15). This precision closely aligns with the correspondence analysis map of the 25 articles selected for this study (Figure 3). It suggests that GPT4o's advanced natural language processing capabilities enable it to effectively discern and respond to the emotional nuances within educational content. The model's ability to capture topics such as "student engagement," "personalized learning," and "educational technology" with high accuracy indicates its potential to generate more relevant and contextually appropriate educational content. This finding is significant, as it highlights the potential of GPT4o to enhance educational applications by providing more emotionally attuned and pedagogically effective responses.

The analysis of the responses from all three LLMs—GPT4o, Kimi, and Gemini—revealed a pattern of association among the Educational AI, Higher Education AI, and Generative AI domains, indicating a complex interplay between these areas within the context of educational content generation. As illustrated in Figures 9, 12, and 15, the models' recognition of these relationships, albeit to different extents, underscores the importance of domain-specific knowledge in shaping AI-generated content.

Future study endeavors will delve into the effects of varying intensities of emotional blackmail within prompts on AI-generated responses. This will be achieved by broadening the literature sample and incorporating diverse prompt-tuning methodologies.

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