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Leveraging search engines and LLMs for creative thinking: effects of prompting skills, and domain knowledge

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Abstract

Introduction. We investigated the effects of domain knowledge (DK) and prompting skills by leveraging a traditional search engine and a prompt-based LLM chatbot for a learning-oriented creative task.

Method. On a simulated curated calligraphy exhibition task for which one must integrate DK and creativity to write summaries of curatorial planning, we observed behavior when using the NPM Collection, Google Search, and ChatGPT. We assessed the creative thinking demonstrated in the final summaries. User perception of tools supporting creative thinking was evaluated by the creativity support index.

Analysis. We analysed information source usage behavior using descriptive statistical analysis and significance testing and used regression analysis to examine the predictive power of tool usage behavior, domain knowledge, and prompting skills for summary writing.

Results. We discovered a positive predictive effect of DK and ChatGPT usage on the quality of curatorial planning summaries. Better prompting skills enhanced task performance and perceived creativity. For creative thinking, Google seemed to better foster exploration than ChatGPT.

Conclusions. Prompt-based LLM chatbots support learning-oriented creative tasks. As prompting skills are essential, prompting should be integrated into information literacy education. The study provides implications for the design of search systems in human–information retrieval–LLM interaction to better support creative tasks.

Introduction

The rapid advancement of large language models (LLMs) has positioned them as a pivotal technology for addressing a wide range of challenges (Noy & Zhang, 2023; Spatharioti et al., 2023; Yilmaz & Yilmaz, 2023; Zhu et al., 2025). Keyword-based search engines (SEs) and prompt-based LLM chatbots employ distinct algorithms and methodologies for interpreting queries or questions and generating responses. Their strengths, however, are mutually complementary. Accordingly, LLM-powered SEs have introduced novel query strategies that facilitate more human-like interactions in information retrieval, forming a new Human-IR-LLM paradigm (Ai et al., 2023; Liu et al., 2024; Zhai, 2024). Pioneering comparative studies examining LLM-based versus traditional search behaviors have begun to emerge (Capra & Arguello, 2023; Wazzan et al., 2024). For instance, Capra and Arguello (2023) designed an interface that integrates SEs with conversational AI using OpenAI's GPT-3.5 API to investigate user search behavior. The study reveals that despite the benefits of conversational AI, some participants expressed distrust in the responses generated by the chatbot and felt the need to verify the information. A few even stated that they considered traditional search engines to be more reliable.

Search activities are not only essential for learning but also play a critical role in idea generation (Chavula et al., 2023; Kules, 2005; Palani et al., 2021). Yang et al. (2025) compared a traditional search engine (SearchOnly) with an integrated platform featuring an AI chat system (Search + Chat) for learning tasks. The study found the AI tool altered user behavior, shifting focus from conventional searches to conversational exchanges. Specifically, the Search + Chat group demonstrated better learning performance with higher normalized gains. These results highlight how conversational AI integration reshapes user behaviors, improves learning outcomes, and provides insights for synergistically enhancing the search-as-learning (SAL) process. Several studies have examined the relationship between creativity and the information search process (Chavula et al., 2023; Palani et al., 2021; Thudt et al., 2015; Zhang & Capra, 2019). However, these studies have primarily focused on user information search behavior for creative learning or idea generation using traditional search engines (SEs) rather than conversational AI tools. In response to the growing need to integrate keyword-based SEs with prompt-based LLM chatbots, this study explores how users engage in search behavior for creative tasks using both SEs and LLM chatbots. We present a study situated at the intersection of Human-IR-LLM interaction, SAL, and search for idea generation, seeking to explore user search behavior during engagement with a learning-oriented creative task. This study draws on the concept of mini-c creativity proposed by Kaufman and Beghetto (2009), which emphasizes the creativity demonstrated in the process of personal knowledge construction. This study contributes to the literature by analysing the behavioral characteristics of users with varying levels of domain knowledge when using Google Search and ChatGPT. It also investigates whether prompting skills compensate for limited domain knowledge and enhance task performance. Our research questions are as follows:

RQ1: How do users' domain knowledge and their use of various information-seeking tools (e.g., Google Search, ChatGPT) affect task performance?

RQ2: What is the effect of users' prompting ability on task performance?

RQ3: What are users' perceptions of utilizing Google Search and ChatGPT as tools to support their creative thinking?

Participants and the learning-oriented creative task

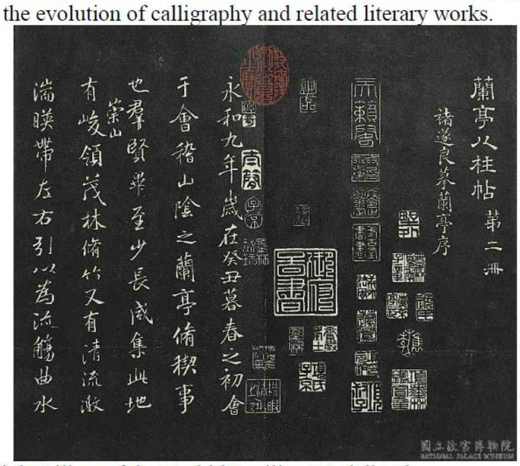
To investigate the effects of users' domain knowledge (DK for short) in executing a learning-oriented creative task using prompt-based LLM tools and SEs, the research targets are ChatGPT and Google Search, which are the most popular tools in our research population. This study specifically focuses on the calligraphy category within the National Palace Museum (NPM) Collection (https://digitalarchive.npm.gov.tw/Collection) in the official NPM website in Taiwan.

We examine how users leverage the strength of both tools and the resources of the NPM website to accomplish a high-level cognitive task which requires creativity.

We recruited twenty-two task participants using purposive and snowball sampling methods. We spent 15-20 minutes introducing our research goals, asked them to read and sign an institutional review board (IRB) approved document (No. C114047) of informed consent to participate, complete the pre-questionnaires, and allowed them to quickly practice using the search systems. Reflecting users with different levels of calligraphy DK and prompting skills in ChatGPT, eleven participants (H_DK) exhibited high domain knowledge and the other eleven participants (L_DK) exhibited low domain knowledge. The H_DK group was composed of participants who were knowledgeable in calligraphy and exhibited a long-term interest in calligraphy learning and exhibitions, whereas the L_DK group was composed of participants interested in calligraphy and calligraphy exhibitions but unversed in calligraphy. In both user groups, three of the eleven exhibited better prompting skills. Accordingly, we further differentiated participants with prompting skills and with different levels of calligraphy knowledge; that is, three participants with high DK and prompting skills (H_DK_P) and three participants with prompting skills but low DK (L_DK_P). The four user groups took a pre-test consisting of multiple-choice questions on calligraphy knowledge, with a maximum score of 100. Their scores, from highest to lowest, were: H_DK_P (100) > H_DK (86) > L_DK (67) = L_DK_P (67).

Mini-c creativity highlights individual insight and originality that emerges during learning and understanding. We simulated a curated calligraphy exhibition task based on mini-c creativity; we referred to this as a learning-oriented creative task. This study used Morae software to record the participants' search and prompting behaviors. Table 1 lists the task scenario and the instructions for writing a summary introducing calligraphy artifacts. The task is designed to engage with resources from the NPM website—particularly its calligraphy collection—while leveraging Google Search and ChatGPT to curate thematic exhibitions and explore the scripts, appreciation concepts, and stylistic diversity of various calligraphers.

Back in middle school, you studied Wang Xizhi's Preface to the Orchid Pavilion, which is hailed as the greatest running script (xingshu) in Chinese calligraphy. Wang Xizhi is also honored as the "Sage of Calligraphy." After viewing his work, you gradually developed an interest in the evolution of calligraphy and related literary works.



Eight Pillars of the Orchid Pavilion Modelbooks
(Source: https://digitalarchive.npm.gov.tw/Collection/Detail/2168?dep=P)

Task description: Please summarize your learning outcomes from the search task. Select 3 to 9 different works from the National Palace Museum collection to curate a themed exhibition. Give your exhibition a title and provide a guided tour-style explanation based on the exhibition's thematic structure. Your explanation should include an integrated presentation of the exhibition concept and key curatorial highlights. You may briefly describe the characteristics of the calligraphic styles and the featured calligraphers. It is not necessary to introduce every single piece in detail.
Instruction 1: Write a 500-word exhibition guide summary that introduces your curated calligraphy exhibition and explains its key themes and highlights.
Instruction 2: Make good use of available resources, including the National Palace Museum Collection, the NPM official website, Google Search, and ChatGPT, to support your research and curatorial planning.

Table 1. Description of the learning-oriented creative task.

Analysis

Herein, we briefly explain the analysis methods to conduct this research. The overall evaluation process is shown in Figure 1.

- ***Observing users' tool usage behaviors:*** The users' tool usage behavior was recorded during the stages of search formulation and source selection and interaction (Vakkari, 2016). The search formulation stage included activities such as keyword searching, field filtering, and prompting. The source selection and interaction stage involved checking and reading the results obtained from either searches or prompts. Notably, these two stages are often intertwined in the information search process and do not necessarily follow a linear progression. The types of prompting include keyword or topic prompting (KTP), question-and-answer prompting (QAP), summarization prompting (SP), fine-tuning prompting (FP), generative knowledge prompting (GKP), chain-of-thought prompting (CoT), expert-based prompting (EP), and self-consistency prompting (SCP) (Walter, 2024). We recorded the resource usage frequency from the NPM Collection, Google Search, and ChatGPT, and calculated the corresponding relative percentages.

- ***Scoring the summaries:*** We invited two experts to evaluate the summaries related to curatorial planning arrangements. This study adopted the evaluation metrics proposed by Wilson and Wilson (2013) to assess the learning demonstrated in the written summaries produced during the simulated knowledge-oriented creative tasks. Specifically, we employed the data quality (D-Qual), data interpretation (D-Intrp), and data criticism (D-Crit) metrics to derive the D score, which corresponds to the cognitive levels of understanding, analyzing, and evaluating/creating in Bloom's taxonomy. D-Qual is used to evaluate the quality of factual information in fulfilling users' information needs, while D-Intrp assesses how users synthesize and associate facts to interpret their meaning. In addition, D-Crit measures users' critical thinking, aligning with higher-order cognitive processes.

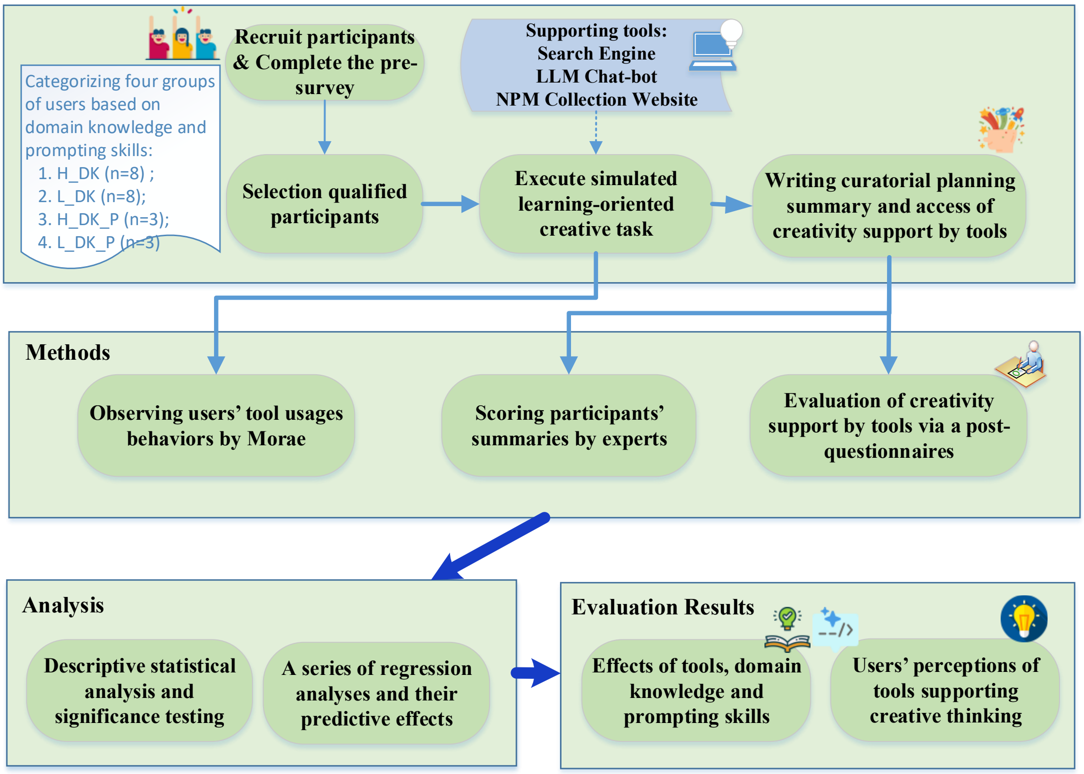


Figure 1. Overall evaluation process.

Creativity support by tools: To evaluate how ChatGPT supports creative thinking, we adopted the creativity support index (CSI), focusing on the dimensions of exploration, expressiveness, immersion, enjoyment, result-worth-the-effort, and collaboration (Cherry & Latulipe, 2014). Note that the collaboration dimension was excluded from this study, as the tasks did not involve collaborative work. A regression analysis was conducted to examine the predictive power of users' tool usage behavior in supporting creative tasks.

Evaluation results

Observing users' information sources usage behaviors

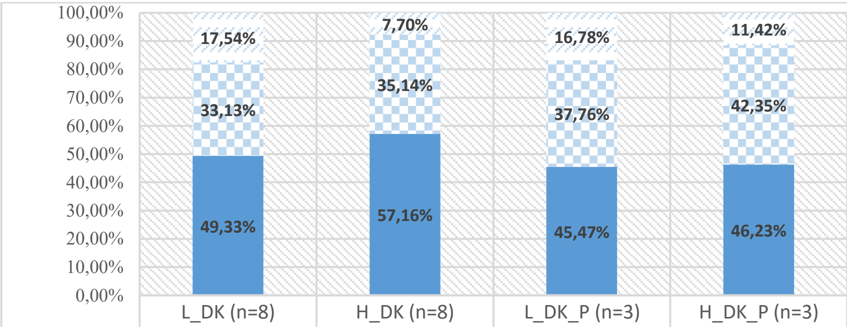
We observed how users accessed resources by retrieving materials from the NPM Collection, searching for information using Google Search, and prompting ChatGPT. Figures 2 and 3 show the relative frequency percentages of the three types of behavior during the search formulation and source selection and interaction stages, as addressed in the previous section.

Search formulation stage

As shown in Figure 2, all user groups exhibited a greater reliance on the knowledge provided by the NPM Collection website. The H_DK group rarely used Google Search (7.70%); in fact, only three users in this group used it at all, and they still achieved relatively normal or good performance. This suggests that these users knew how to strategically integrate information from various sources to construct meaningful knowledge.

For users with weaker prompting skills, users of both H_DK and L_DK groups frequently used keyword or topic prompting (KTP). The H_DK group often adopted topic prompting and then fine-tuning prompting (FTP) when writing summaries. The L_DK group used keyword prompting and question-and-answer prompting (QAP) interchangeably when summarizing content. Three out of sixteen users employed generative knowledge prompting (GKP), but this did not necessarily result in better scores. Other prompting strategies did not appear during the interaction process. We adopted Welch's ANOVA to compare the differences in prompting skills between the L_DK and H_DK groups. The results showed a marginally significant difference in FTP usage (F = 4.797, p = 0.046). This reveals that the H_DK group effectively utilized KTP first and then refined the responses using FTP. In addition, they may have possessed more prior knowledge; thus, they knew how to express affirmative keywords or concepts, thereby enabling them to fine-tune their queries through ChatGPT.

For users with better prompting skills, users of both H_DK_P and L_DK_P groups adopted FTP frequently and then KTP prompting skills. Users who knew how to utilize chain-of-thought (CoT) or expert-based (EP) prompting achieved higher scores. The results show that users with better prompting skills adopted more kinds of advanced skills leading to superior performance.



	L_DK (n=8)	H_DK (n=8)	L_DK_P (n=3)	H_DK_P (n=3)
Google	17,54%	7,70%	16,78%	11,42%
ChatGPT	33,13%	35,14%	37,76%	42,35%
NPM	49,33%	57,16%	45,47%	46,23%

Figure 2. Relative frequency percentages of three types information usage behavior for search formulation

Source selection and interaction process

Regardless of the user group, Google Search was the least used tool, as shown in Figure 3. Interestingly, the L_DK_P group relied more on GPT prompting (56.12%) to accomplish the task compared to the other groups of participants. The other three groups exhibited similar tool usage frequencies. Statistical analysis shows that ChatGPT usage in the L_DK_P group was significantly higher than that in the H_DK_P group; however, for the NPM Collection website, the L_DK_P group exhibited significantly lower usage than the H_DK_P group. The results reveal that the ChatGPT tool altered users' Google search behaviors across all task stages, shifting the focus from conventional SEs to conversational exchanges. This finding aligns with Yang et al.'s (2025) study.

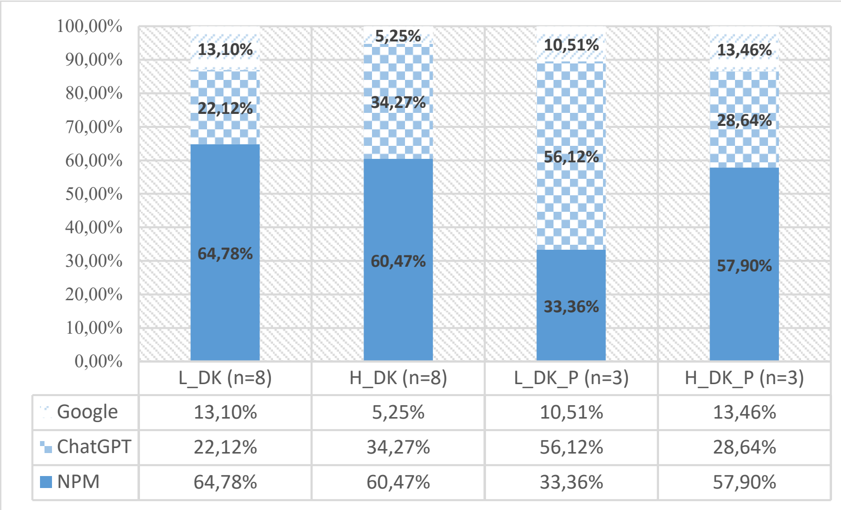


Figure 3. Relative frequency percentages of the three types information usage behaviors for source selection and interaction

Scoring the summaries of curatorial planning

We asked two experts to evaluate each user's D score based on the D-Qual, D-Intrp, and D-Crit metrics. Each aspect was rated on a scale from 0 to 2, yielding a maximum total D score of 12 by summing the scores from both experts. Tables 2 and 3 present the detailed results for each group of users.

The L_DK_P group achieved the highest average D score, with the overall ranking being L_DK_P > H_DK_P > H_DK > L_DK. The L_DK_P group demonstrated significantly higher cognitive performance (D_score) than users without prompt engineering training (L_DK and H_DK groups) ($F = 3.242$; vs. L_DK: $p = 0.018$; vs. H_DK: $p = 0.035$). These results suggest that the L_DK_P group even outperformed the H_DK group, indicating that prompting skills compensate for a lack of domain knowledge.

Groups	**No prompting skill (L_DK #)**								**Better prompting skill (L_DK_P #)**		
Users	L_DK_01	L_DK_02	L_DK_03	L_DK_04	L_DK_05	L_DK_06	L_DK_07	L_DK_08	L_DK_P_09	L_DK_P_10	L_DK_P_11
D_score (ranking)	2(22)	5(16)	7(8)	5(16)	6(13)	7(8)	7(8)	8(6)	7(8)	**10(1)**	**10(1)**
Average	**5.875**								**9.000**		

Table 2. Low domain knowledge group without or with prompting skill.

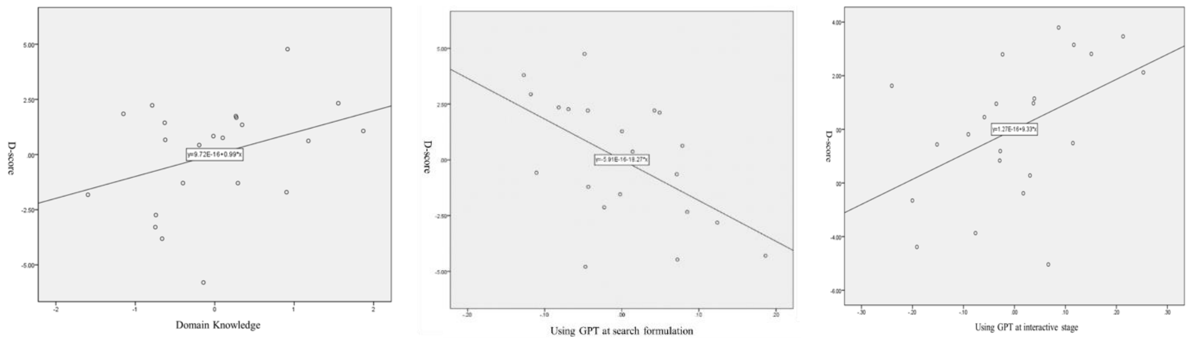
Groups	**No prompting skill (H_DK #)**								**Better prompting skill (H_DK_P #)**		
Users	H_DK_01	H_DK_02	H_DK_03	H_DK_04	H_DK_05	H_DK_06	H_DK_07	H_DK_08	H_DK_P_09	H_DK_P_10	H_DK_P_11
D_score (ranking)	5(16)	5(16)	5(16)	7(8)	8(6)	9(4)	6(13)	5(16)	6(13)	9(4)	**10(1)**
Average	**6.250**								**8.333**		

Table 3. High domain knowledge group without or with prompting skill.

Influence of users' tool usage behavior on task performance

Among the information gathered from Google Search and ChatGPT, users preferred to adopt ChatGPT to accomplish the task, as addressed in the previous subsection. Accordingly, we conducted a regression analysis to examine the predictive power of relevant variables on task performance, i.e., the D-score. We adopted a multiple linear regression model to examine whether domain knowledge, ChatGPT usage for the search formulation stage, and ChatGPT usage for the source selection and interaction stage could predict cognitive performance (D-score). The results indicate that the overall model was statistically significant ($p = 0.005$), with an adjusted R^2 of 0.416, suggesting that the model explains 41.6% of the variance in D-scores. We likewise examined the predictive power of using the NPM Collection, as it was frequently accessed by the participants. The results showed that the model failed to reach statistical significance ($p = 0.066$). In addition, the usage of NPM resources exhibited a moderate negative relationship with the D-score.

Of the three predictor variables, domain knowledge exhibited a significant positive effect on task performance, as shown in Figure 4(a), suggesting that participants with higher prior knowledge tended to perform better. In contrast, ChatGPT usage for the search formulation did not significantly predict performance, as shown in Figure 4(b), indicating that merely using ChatGPT for search prompts was not sufficient to improve outcomes. However, ChatGPT usage for the resource selection and interaction demonstrated a positive predictive effect, as shown in Figure 4 (c), implying that actively engaging with and integrating ChatGPT-generated content contributed to enhanced task performance.



(a) Effects of domain knowledge (b) Using GPT at the search formulation stage (c) Using GPT at the interactive stage

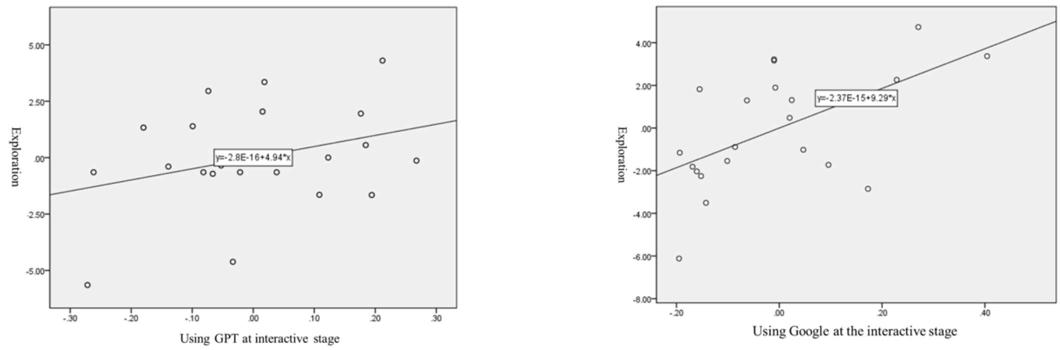
Figure 4. Predictive effect on three predictor variables for D_score.

Users' perceptions of tools supporting creative thinking

This study adopted CSI as developed by Cherry and Latulipe (2014) from the perspectives of the dimensions of exploration, expressiveness, immersion, enjoyment, and results-worth-the-effort to evaluate the effectiveness of ChatGPT in supporting creative thinking. Each dimension was rated on a 0–100 scale using a pair of contrasting statements. In addition to these ratings, participants made paired comparisons to determine the relative weights of each dimension. The final CSI score was calculated as the weighted average of dimension scores.

The results show that groups with prompting skills perceived ChatGPT as supportive of creative thinking. Specifically, the CSI scores of the L_DK_P and H_DK_P groups were 78.33 (SD = 10.07) and 72.17 (SD = 12.41), respectively. In contrast, the CSI scores of the L_DK and H_DK groups were 71.19 (SD = 15.44) and 66.94 (SD = 20.46), respectively. The H_DK group of users was the least likely to perceive ChatGPT as supportive of the creative thinking task. This may suggest that these users preferred to rely on their prior knowledge to complete the tasks rather than utilize ChatGPT. Across the five CSI dimensions, participants generally perceived ChatGPT as most supportive in the area of exploration and least supportive in immersion. The overall ranking across the five dimensions, from highest to lowest, was exploration, enjoyment, expressiveness, results-worth-the-effort, and immersion.

Since ‘*exploration*’ was generally perceived to be the most positive experience factor of creative thinking, a regression analysis was conducted to examine the predictive power of user behavior on these two factors. The regression model results show that usage of ChatGPT and Google Search during source selection and interaction exhibited a positive predictive effect on the experience of ‘*exploration*’, as shown in Figures 5(a) and 5(b). The overall model reached a significant level ($p = 0.014$) with an adjusted R^2 of 0.295. Based on Figures 5(a) and 5(b), the study found that for the exploration factor, the usage of Google exhibited a stronger positive relationship than that of ChatGPT. Specifically, the regression slopes in Figure 5(b) (Google–Exploration) are noticeably steeper than those in Figure 5(a) (ChatGPT–Exploration). This suggests that Google usage is strongly linked to exploratory behavior, as users tend to extend searches for open-ended information, thereby enhancing the exploration experience.



(a) Using GPT at the interactive stage

(b) Using Google at the interactive stage

Figure 5. Predictive effect on experience of exploration during source selection and interaction.

Conclusions

This study contributes to the literature by analysing the behavioral characteristics of users with varying levels of domain knowledge and prompting skills when using Google Search and ChatGPT for a learning-oriented creative task. We found that users with high domain knowledge or frequent ChatGPT use during the source selection and interaction stages positively predicted the quality of curatorial planning summaries (D-score). Additionally, users with better task performance demonstrated strategic use of both information-seeking tools and prior knowledge from the NPM Collection website to accomplish the task. Our findings also suggest that strong prompting skills can compensate for limited domain knowledge and enhance task performance. Furthermore, users with higher prompting skills perceived ChatGPT as more supportive of creative thinking. Interestingly, search engines such as Google appear to play a more influential role in fostering creative search outcomes, particularly in enhancing an exploratory mindset. Tibu et al. (2024) adopted the Efficient Search Tactic Identification (ESTI) method to map search tactics onto a stratified grouping model. Their work repurposes traditional search tactics as strategies for prompt-based interactions and provides valuable guidance for our future research examining user prompting strategies and their influence on creative thinking. We acknowledge that the small sample size may introduce potential bias. To address this limitation, we plan to expand the scale of the evaluation and provide the interview coding results in future work. This study offers a foundational reference for the Human–IR–LLM interaction field, particularly in the context of creative thinking.

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