Information foraging in human-ChatGPT interactions: factors of computational thinking dissociate exploration and exploitation

Pablo Flores (pablo.flores@helsinki.fi)
Faculty of Educational Sciences, University of Helsinki
Siltavuorenperger 5a, Helsinki, 00014 Finland

Guang Rong (guang.rong@helsinki.fi)
Faculty of Educational Sciences, University of Helsinki

Ben Cowley (ben.cowley@helsinki.fi)
Cognitive Science, Faculty of Arts, University of Helsinki
Faculty of Educational Sciences, University of Helsinki

Abstract

LLMs can interact as though they understand language, yet they remain algorithms and can be used as such. This study explores a novel guided interaction design for modeling users' information foraging behavior when navigating GPT-generated content and the role of Computational Thinking skills in shaping such behavior. Conducted with nine educational researchers in a doctoral-level AIEd course, our research used editable prompt templates and keywords to structure the prompt crafting process. We modeled and analyzed participants' behaviors in terms of *exploration* (to generate and explore various information landscapes) and *exploitation* (to delve deeper in a specific landscape). Our data, including responses from the Computational Thinking Scale, suggests that Algorithmic Thinking and Creativity might encourage exploitation behavior, leaning more on AI-generated information rather than pre-defined design elements.

Keywords: ChatGPT 4; Large Language Models; Human-LLM interaction; Information Foraging; Computational Thinking

Introduction

Information Foraging Theory (IFT) has been useful in modeling users' goals and behaviors in web navigation. These models have been useful in driving web design, as they leverage users' existing knowledge and enhance efficiency in foraging tasks. Such models also help to explore and understand the ways technology affects human navigation within information landscapes and sensemaking processes (Chi et al., 2001; Kittur et al., 2013; Pirolli & Card, 1999; Russell et al., 1993). Information foraging agents are constantly balancing between spending their resources (time, attention, memory) on *exploring* for novel sources of information and *exploiting* those they already know about. These types of decision making are visible in their task behavior and actions (Cohen et al., 2007; Hills et al., 2015; Pirolli, 2005, 2007).

Given that ChatGPT has contextual memory of the conversation, it enables users not only to generate scenarios but also to coherently delve deeper by prompting for additional details, thus enriching the scenario with more information. This dynamic closely mirrors the two fundamental information foraging decisions: *Exploration*, where agents search new information landscapes (ChatGPT generates scenarios and we read them), and *Exploitation*, where agents utilize a landscape to its full potential (we ask ChatGPT to further elaborate an interesting scenario) (Cohen et al., 2007; Hills et al., 2015; Todd & Hills, 2020). This tradeoff is experienced on older digital interfaces in a similar way, but ChatGPT offers the novel aspect of convincing natural language interaction. Yet unlike an interaction with a human, ChatGPT is still an algorithm and can be exploited as such. These factors prompt the question: how does computational thinking skill modulate a person's information foraging behavior in goal-directed interaction with ChatGPT?

We here report a study to examine this question, where we conducted a controlled interaction between subject-matter experts (doctoral researchers in a higher-education course) and ChatGPT, with a shared specific goal (creation of personalized course content).

Our controlled interaction design aimed to systematically analyze humans' decision-making when foraging in novel AI-generated information landscapes. The design enabled participants to generate personalized course assignment scenarios through the use of editable *prompt templates* and a set of *keywords*. These *prompt templates* facilitated the behavioral modes of IFT, standardizing the interaction across participants and enabling for systematic analysis of their foraging behavior.

The role of computational thinking Skills in modulating interactions with ChatGPT is underexplored. In a seminal contribution, Wing (2006) underscored the importance of Computational Thinking skills, which enables people to solve tasks in a similar way that computer algorithms work and are beneficial across most professional domains. Since then, computational thinking skills have grown into a cornerstone of digital education research and some work suggests that they correlate with more confident and efficient use of digital technologies (Cansu & Cansu, 2019; Grover & Pea, 2013; Shute et al., 2017). Regarding its influence on Human-AI interactions, Celik (2023) explored the determinants of AI literacy, which encompass the knowledge for using, recognizing and evaluating AI-based tools, and reported a significant correlation with computational thinking skills. Yilmaz and Karaoglan Yilmaz (2023) also found, by controlled experiment, that using ChatGPT in a programming course improved students' computational thinking skills.

In L. K. Samuelson, S. L. Frank, M. Toneva, A. Mackey, & E. Hazeltine (Eds.), *Proceedings of the 46th Annual Conference of the Cognitive Science Society.*

RQ1. How do students interact with ChatGPT-4 in terms of Exploration-Exploitation decision-making?

RQ2. How are students' Computational Thinking Skills reflected in their interactions with ChatGPT-4?

Methods

Participants We conducted this study within an international doctoral course called "Basics on Artificial Intelligence in Educational Sciences" at the University of Helsinki. Participants (n = 9), ranged in age from 30 to 40 (mean = 32.8) and were almost gender balanced (5 females). Five of them reported previous experiences in using ChatGPT for work

Interaction Design Our design consists of six editable *prompt templates*, divided in two types; and a set of 86 *keyword cards* distributed unevenly in seven different categories, representing different concepts contextualized within their course assignment.

The prompt templates were divided between *Exploration* and *Exploitation* prompt types. *Exploration* prompts were designed to create the assignments' scenarios through a fixed imperative sentence, like "Predict me a future where..." or "Describe me a scenario where...". In the subsequent editable part of the prompt, participants could combine from four to six keywords to shape the scenario to their interests. *Exploitation* prompts were designed in a similar fashion, but focused on a created scenario, following structures like "Tell me more about this scenario, but put more emphasis on ....". The subsequent editable part was restricted to one or two keywords. The design used a categorized pool of keywords shared between participants that were contributed by participants in the course. These categories were roughly defined beforehand, based on a general separation of concepts involving AIEd scenarios, like "Actors", "AI tools", and "Subject". The keywords were not all initially displayed and participants viewed more as they required them. This followed from Cowley et al.'s (2023) concept of a socially-shared virtual environment that allows users to explore their own representation. Furthermore, to explore AI's influence in participants' foraging behavior, they had the option to use keywords sourced from the AI-generated information.

With these elements, participants crafted a diversity of prompts tailored to their interests, which were used to create and elaborate their personalized assignments' scenarios in ChatGPT. The interaction diagram in Figure provides a visual representation of this process.

Computational Thinking Lastly, following Celik's (2023) and Yilmaz and Karaoglan Yilmaz's (2023) work, we employed the Computational Thinking Scale (CTS; Korkmaz et al., 2017). Being adapted for clarity, we recalculated Cronbach's Alpha for the aggregated scale (0.65) and the 5 subfactors: Creativity (0.63), Algorithmic Thinking (0.9), Cooperativity (0.9), Critical Thinking (0.95), and Problem Solving (0.7).

Table 1: Behavioral variables describing participants' interaction with ChatGPT

Code	Description
Exploration	N° of exploration prompts used
Exploitation	N° of exploitation prompts used
Viewed Kw	Max. rows of keywords participants managed to see during the interaction.
Guide's Kw	N° of used keywords sourced from the design
GPT's Kw	N° of used keywords sourced from the GPT-generated text
Own Kw	N° of used guide's keywords that the participant provided to the design
Other's Kw	N° of used guide's keywords that the participant did not provided to the design.
Time	Time length of the interaction, measured from the first prompt to the last.

Data Analysis We coded the behavioral data from the interactions using ATLAS.ti 23. A frequency-based data set was constructed based on the interaction logs provided by ChatGPT. The data set encompassed 8 variables, which described the user choices derived from the prompt templates, keywords, and students' reported interests. (see Table 1).

Both the CTS and the interaction data were then analyzed within R statistical computing environment.

To examine participants' foraging behavior, we used descriptive statistics to analyze participants' prompt construction and keyword usage. To explore the potential associations between participants' interactions and their Computational Thinking skills, we employed network analysis methods.

We estimated the network structure by first calculating a Kendall's tau (1949) correlation matrix from the interaction and CTS data. To minimize spurious edges, we set a standard statistical significance threshold of $p < 0.05$ and adjusted the correlation strength with a lower threshold of $\tau > 0.4$, based on Dancey & Reidy's (2007) correlation strength interpretation in psychological studies. We estimated edge weight stability with bootstrapping methods (Efron, 1992; Hevey, 2018). We used non-parametric bootstrap (resampling with replacement) to create 2500 bootstrapped samples. We then estimated the edge weights' mean and Confidence Intervals (CIs) for these bootstrapped samples, defining the CIs as twice the standard deviation.

Results

Exploration and Exploitation

The interactions extended from 4 to 30 minutes (M = 14.79 minutes , SD = 8.58) and from two to six prompts (M = 3.78, SD = 1.39). The results show that the total count of exploitation prompts is higher than exploration prompts (Table 2), with only two participants using more exploration than exploitation prompts. Participants used a maximum of two

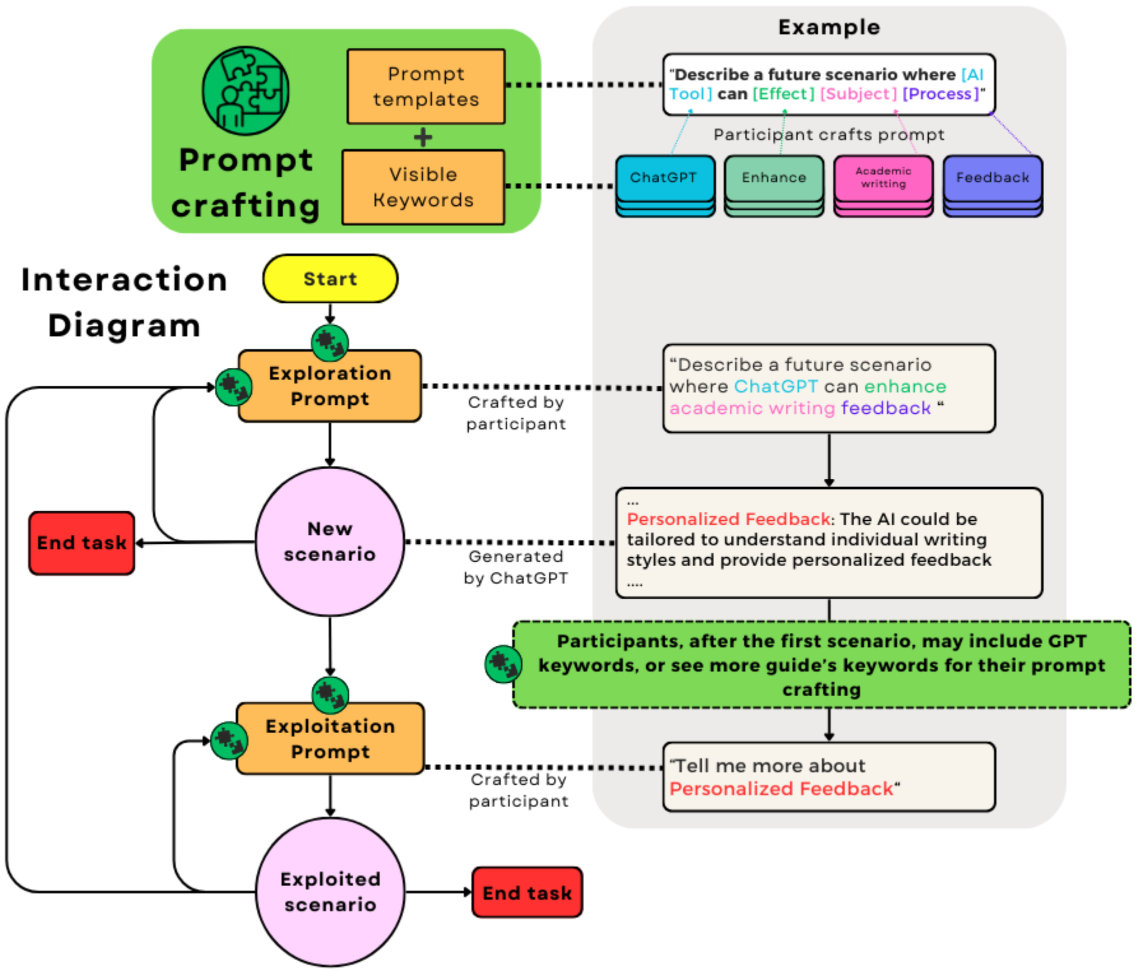

Figure 1: Interaction Diagram. Participants craft their prompts by selecting a prompt templates and keywords of interest. The process initiates with an *Exploration* prompt, to generate a hypothetical assignment scenarios. Subsequently, participants can select new templates and keywords, and craft prompts to *explore* new scenarios, *exploit* interesting scenarios, or end the task by choosing a scenario that is interesting for them. After viewing the first scenario, participants may view additional guide keywords or include GPT's keywords into their prompt crafting. Note: The examples provided are simplified; actual prompts and ChatGPT's responses are more detailed.

exploration prompts, split almost equally between those that only explored one initial scenario, and those that explored an extra one. In contrast, there is more variability in the use of exploitation prompts. Almost every participant –except from one– executed at least one exploitation action. No participant stopped at the minimum possible number of actions (generating and selecting an scenario without further prompting). Despite a suggestive greater use of exploitation prompts between participants that only explored once (M = 3.0, SD = 1.8) instead of twice (M= 1.6 , SD = 1.4), there was no significant difference (Mann-Whitney U = 14.5, p = .89). Lastly, Table 3 shows that the use of exploitation prompts is more frequent in the selected scenarios, instead of the discarded ones.

Separating by prompt type, exploration prompts exclusively incorporated guide's keywords, whereas exploitation prompts mainly employed GPT's keywords, identified within

Table 2: Overall use of prompt types and used keywords. No prompts were constructed with a mix of Guide and GPT' keywords.

Prompt type	Total uses	Prompts with Guide's Kw	Prompts with GPT's Kw
Exploration	14	14	0
Exploitation	20	8	12

Table 3: Use of exploitation prompts in selected and discarded scenarios.

Scenario	Total exploitation prompts used	Scenarios exploited	Scenarios with GPT's Kw
Selected (n = 9)	18	8	6
Discarded (n = 5)	2	1	1

the generated scenarios (Table 2). Individually, results show that 7 out of 8 participants that used exploitation prompts used at least one GPT's keyword with them. Lastly, Table 3 shows a predominant presence of both exploitation prompts and GPT's keywords within the selected scenarios, contrary to the discarded ones.

Regarding the use of the guide's set of keywords we found that, overall, most of the guide's keywords used by participants corresponded to other's keywords, not personally provided by the participant, instead of their own (66 our of 89). Regardless, we also observe that most participants, except for two, included at least one of their own keywords in their prompts. All in all, although inspired by the idea from Cowley et al. (2023) of using a socially-shared environment to allow users to explore their own representation, our study sessions did not support rich enough interactions to provide strong data on this question.

Associations with Computational Thinking

Figure 2 shows on the relations between behavioral variables and the CTS's sub-factors. This network was made up of 13 nodes, mean edge weight was 0.089, and 24 out of 78 possible connections were observed consisting of 30.8% of all possible connections. Figure 3 shows estimated edge weight stability for the expanded network. There are three edges with CIs above zero: the amount of viewed keyword cards negatively relates both to creativity (tau = -0.76, p = .014) and algorithmic thinking (tau= -0.76, p = .014) sub-factors' scores, and the use of own keywords is negatively correlated with creativity sub-factor's scores (tau = -0.65, p = .022).

Discussion

We examined how doctoral researchers display information foraging (RQ1) and computational thinking (RQ2) when using ChatGPT for a pedagogical design task. Considering the small and non-representative nature of our sample, we focus our study on exploratory analysis and generating hypotheses.

RQ1: Information Foraging Behavior

Our study of students' interactions with GPT-4 in creating personalized case scenarios offers fresh insight to the application of IFT in the context of AI-generated information landscapes.

In our study, participants' foraging behavior was driven by information scents identified both in the interaction design and in the AI-generated text. Helpful in modeling foraging behavior, information scent can be briefly described as the subjective value of seen information in respect to the agent's inner goals, usually driving foraging decision-making (Pirolli, 1997; Spool et al., 1998).

We did not find a negative correlation between *exploration* and *exploitation* prompts. Nevertheless, we found clear differences in how the two prompt types were constructed, primarily due to the distinct sources of the keywords employed

Exploration prompts These prompts were exclusively constructed using the guide's set of keywords derived from participants' interests (Table 2). Notably, participants frequently opted to include keywords contributed by others, instead of their own. This suggests a deviation from the intuitive pattern where participants' own interests would be a main driver in their foraging behavior. Instead, we observed a predominant inclination towards a shared conceptual space over the set of keywords.

This finding suggests a meaningful social process, where participants' exploration efforts were influenced by a collective conceptual space, gathered by the keywords, rather than being driven solely by personal interests. In other words, participants might assign greater value to others' mental schemas, seen in their keywords use, and tend to begin their foraging task following those information scents. Prior IFT research showed how social cues in web design can effectively enhance users' foraging performance and promote shared sense-making of tasks (Cress et al., 2013; Fisher et al., 2012; Held & Cress, 2010; Held et al., 2012). Kittur et al.'s (2014) study illustrates how digital designs encapsulating mental schemas that appeal to others can enhance the foraging process. They showed that, when social cues are present, users would converge faster on the relevant dimensions of a task. They would leverage other users' mental schemas, enabling them to follow information scent trails of previous users. Similarly, incorporating elements collecting social cues in human-LLM interaction designs might influence foraging behavior within AI-generated landscapes in a similar way.

Exploitation These prompts occurred slightly more frequently than Exploration ones (Table 2), and converged in the selected scenarios (Table 3). This trend suggests that exploiting the scenarios possibly added value to them, influencing the decision-making process in task completion and scenario selection. This suggestion aligns with the IFT definitions, where exploitation is viewed as a means to utilize and enrich an informational landscape to its fullest (Cohen et al., 2007; Hills et al., 2015; Pirolli, 1997).

Regarding the keywords used in exploitation prompts, we found that there was a clear preference for using GPT's keywords (See Table 2). This predominance suggests that, as the interaction progressed into the exploitation prompts, participants relied more on the AI-generated information for scents to follow, diverging from the guide's keywords guidance. It's important to note, however, that this shift towards AI-generated content still occurred within the context established by the initial exploration prompt. The specific and contextual nature of GPT's keywords helped refine and specify elements within generated scenarios. In essence, exploitation prompts may not only add value to AI-generated content, but this value may be largely derived from information scents identified within the AI-generated landscape. The following section offers some suggestions on how participants might discern the value of the different sources of information.

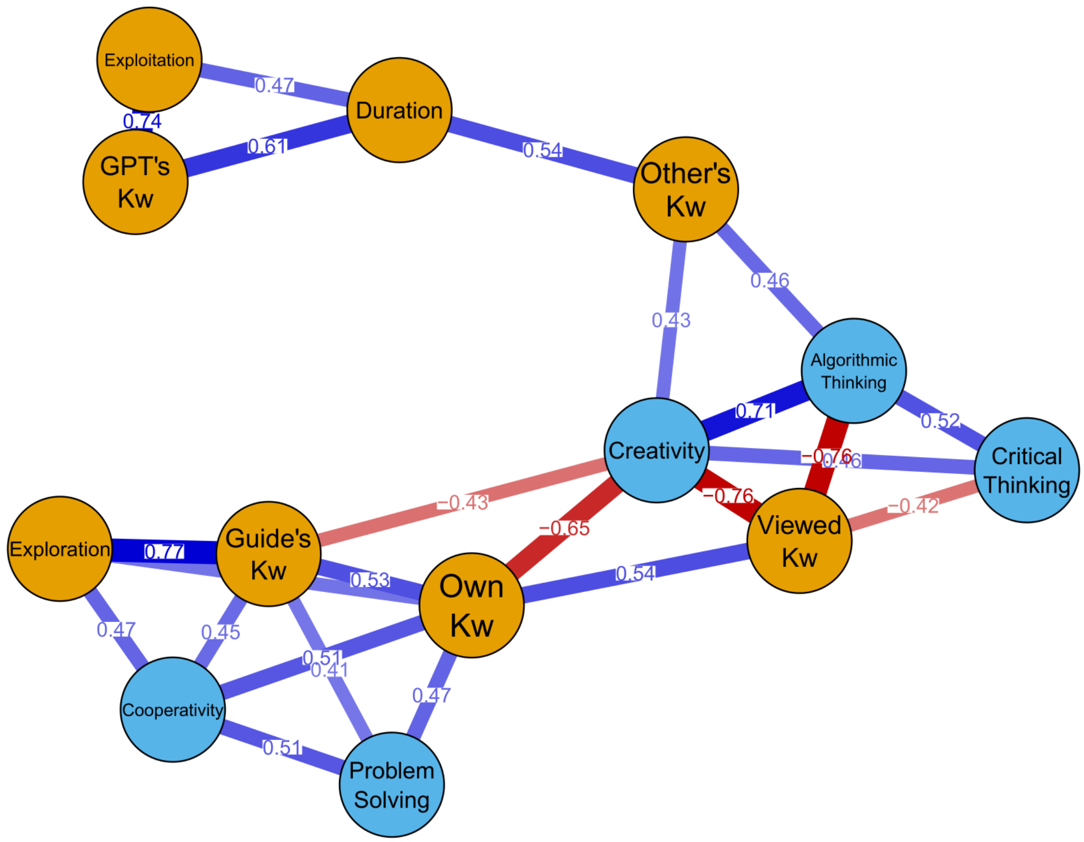

Figure 2: Estimated network structure between the behavioral variables and the CTS sub-factors' scores. Nodes symbolize variables: Yellow for Interaction Behaviors, Blue for Computational Thinking Survey's (CTS) sub-factors. Edges represent Kendall's tau correlations: Blue for positive, Red for negative. Spurious edges are filtered based on strength and significance, with thresholds set at $\tau > 0.4$, $p < 0.05$.

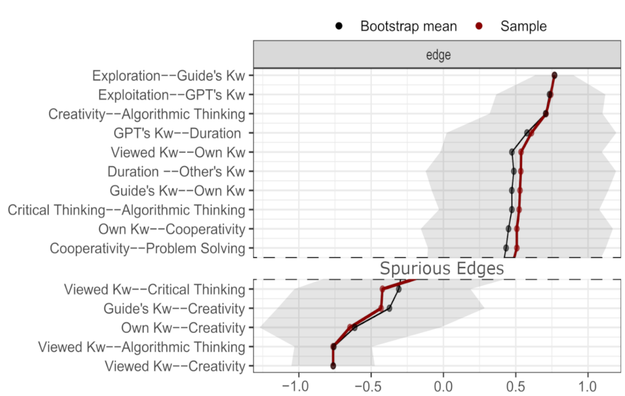

Figure 3: Estimated edge weights' accuracy. Estimated weights (red) compared to bootstrapped estimates (black) and their CIs (gray area). Estimates of spurious edges removed.

RQ2: Computational Thinking in Human-ChatGPT interaction

Our network analysis results suggest a clear distinction between exploration and exploitation prompt usage. As previously noted, exploration prompts uniquely use guide's keywords, whereas exploitation prompts are more aligned with GPT's keywords. Our estimated network delineates two distinct node clusters: one for exploration and another for exploitation, with the sub-factors of creativity and algorithmic thinking emerging as key elements in separating these clusters (See Figure 2). These factors show a negative correlation with the number of viewed keywords and a strong positive correlation with each other. Importantly, they are the only observed correlations between the behavioral and CTS data with CIs above zero (See Figure 3). Consequently, the subsequent sections will explore how creativity and algorithmic thinking potentially influence foraging behavior and prompt construction in human-LLM interactions.

Creativity In the context of IFT, the amount of viewed keywords indicates the volume of conceptual information available for prompt construction, chosen based on assessed subjective value, or information scent. This negative correlation between available information and their self-reported creativity suggests that participants with higher creativity scores may rely less on guide's keywords for prompt construction, and their scenario co-creation task.

Participants with higher creativity scores, possibly more open to experimenting with new ideas, showed a tendency to use keywords different to their own ones. In contrast, those with lower creativity scores seemed to prefer the more structured guidance of our design, viewing more keywords and gravitating towards the ones aligned with their interests, as suggested by our network analysis.

While creativity is often seen as a fuzzy and ill-defined concept (Henriksen et al., 2018; Mishra & the Deep-Play, 2012), technological innovations have arguably enhanced and broadened the ways humans can imagine, act and express themselves (ISTE, 2015; Zhao, 2012). Supporting this, Shakeri et al.'s (2021) pilot study on collaborative creative writing found that GPT, when acting as a co-writer, relieved creative pressures for users. By leaning on AI-generated suggestions (i.e., GPT's keywords) to continue their stories, users engaged in an AI-assisted discovery process while retaining a sense of ownership over the story.

Building on these ideas, it seems that more creative users may pay less attention to the interaction designed elements, focusing instead on the novel conversational dynamics offered by ChatGPT. Conversely, less creative participants may rely more on the design-provided guidance. This hypothesis is partially supported by a positive correlation with the exploitation cluster, driven predominantly by GPT's keywords, and a negative correlation with the exploration cluster, dominated by guide's keywords (See Figure 2).

Algorithmic Thinking Reflecting the trends observed for creativity, our results suggest that participants with higher scores in algorithmic thinking also required less available information from the guide's keywords in their foraging task, as well as showing an increased use of others' keywords 2.

Algorithmic thinking, the skill of understanding, applying, assessing, and producing algorithms (Hromkovic et al., 2017), is central to computational thinking. It is a key skill for computer science professionals (Angeli & Giannakos, 2020; Cansu & Cansu, 2019; Wing, 2006) and is integral to human-computer interactions, especially given the functional nature of computers that typically require automated, sequential, iterative, and logical instructions.

In AI-based systems, where machine learning methods rely on somewhat different principles, such as big data and probabilistic models, this definition may require adaptations (Ferreira et al., 2019; Tedre et al., 2021). Nevertheless, prompting involves an abstraction and automation process where users iteratively design, modify, and test different prompts to achieve desired outcomes, resembling processes of algorithmic thinking (Repenning & Grabowski, 2023).

Building on these considerations, our findings might suggest that participants with higher algorithmic thinking scores required less guidance from the pre-defined design keywords to construct effective prompts. They may possess a better understanding of prompting as the primary mode of interaction with ChatGPT. As Repenning & Grabowski (2023) note, prompting often requires multiple iterations for optimal results (i.e., following the conversation, or exploiting). This process may also be guided by ChatGPT's conceptual suggestion, as seen also in the studies by Yilmaz & Karaoglan (2023) and Shakeri et al. (2021) where participants tended to off-load creative and mechanical efforts thanks to the support of GPT's suggestions (i.e., GPT's keywords). These observations are slightly supported by algorithmic thinking scores positive association with the exploitation cluster in our estimated network (See Figure 2). In other words, participants with higher algorithmic thinking might place greater value on exploiting ongoing conversations, as opposed to exploring new scenarios, to refine their AI-generated content. Furthermore, they could more rapidly discern the specific and contextual value of GPT's keywords for crafting effective exploitation prompts.

However, both algorithmic thinking and creativity subfactors show no direct associations with any specific prompt types, and further, larger scale studies are needed to enrich our findings.

Limitations and Further Lines of Research

Our study's primary limitation is its small sample size, which limits our ability to identify subtle relationships and increasing the possibility that our findings might differ from other samples. However, the structured and guided nature of our interaction offers opportunities for digital implementation, allowing for scalable and adaptable use across different domains. This open avenues for replication studies in diverse settings an populations. A following limitation is our exclusive focus on quantitative data. This approach restricted our analysis to observable factors. For a deeper understanding in users' foraging behavior, mixed-methods approaches incorporating both quantitative and qualitative data are required. A deeper focus on algorithmic thinking and creativity in human-LLM interactions may be of special interest. Potential instruments include the Creativity Support Index (Cherry & Latulipe, 2014) for measuring digital technologies' support in creative processes, and the Algorithmic Thinking Test for Adults (Lafuente Martínez et al., 2022) for a focused measuring of algorithmic thinking within computational thinking.

Understanding user behavior in AI-generated information landscapes is key to developing intuitive, efficient, and user-centric AI systems. Aligning prompt construction and analysis with human foraging behaviors models might significantly improve our understanding of information foraging process within the novel AI-generated landscapes. Furthermore, integrating social cues that collect and aggregate users' mental schemas in human-LLM interaction designs, inspired by Kittur et al.(2014), could enhance users' foraging process and allow for deeper understanding of social sense-making processes on various knowledge domains and tasks.

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