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Human-AI Interaction with Large Language Models in Complex Information Tasks: Prompt Engineering Strategies

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Abstract: This article explores human-AI interaction with large language models or conversational agents in complex information tasks with a focus on prompt engineering strategies. The paper reviews the current literature on the use of artificial intelligence (AI) for complex information tasks that are often nonlinear and entail interpretation, organization, and synthesis of information. Building on the role prompting plays in enhancing generative AI responses, the study frames prompt engineering as a medium with the potential to enable users to iteratively tackle complex information tasks. It provides recommendations for the use of key prompting strategies such as task decomposition, iterative refinement, identification of audience and context, and role/persona assignment. Considering the notable importance of prompting as a critical AI literacy, the paper ends with several implications that might be conducive to enhance the human-AI communication in generative AI context.

Keywords: Generative AI, human-AI interaction, large language models, prompt engineering, complex information tasks, AI literacy, prompting strategies

Highlights

What is already known about this topic:

- Large language models (LLMs) have considerably shifted the ways users interact with computers.
- LLMs are widely used in the context of information exploration in human-AI interaction.

What this paper contributes:

- Prompt engineering techniques (e.g., Chain-of-Thought prompting) enhances human-AI interaction
- Prompt engineering strategies allows more accurate and useful outputs in complex information tasks.

Implications for theory, practice and/or policy:

- The ability to craft effective prompts becomes a critical skill for both personal and work environments.
- Prompting techniques should be implemented in real-world scenarios.

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Introduction

Natural language is the most congruent medium of communication to human beings, manifesting so far itself mostly in in-person or computer-mediated communication. However, recent developments in natural language processing and machine learning have considerably shifted the way humans interact with computers. Human computer interaction has started relying heavily on natural language user interfaces in which interaction takes place primarily in strings of texts in natural language (Følstad & Brandtzæg, 2017). A contemporary example of such interaction is visible in the recent chatbots – also known as conversational AI, conversational agents, digital assistants, AI assistants, or bots - powered by generative Artificial Intelligence (AI) such as ChatGPT and Gemini. The fundamental building block to recent chatbots has been fueled by Large Language Models (LLMs) trained on massive corpora of texts capable of performing new tasks in response to textual prompts or from a couple examples (Touvron et al., 2023).

A crucial feature of large language models is their ability to engage in natural conversations with human users in human-like fashion as they have been trained on human language and discourse. The exponentially increasing size of training data and the number of parameters allow LLMs to be adapted to various domains from education to healthcare and to customer service. A notable function of LLMs exhibited in well-known generative AI applications is that they can process a large amount of input and produces an output as a response. Because LLMs have been trained on massive human language data, the underlying transformer model predicts likely response and yields a response to the query by the user (for details see Jurafsky & Martin, 2021). In this way, LLMs can hold a conversational thread in a natural conversation with a human user. As opposed to mainstream interaction patterns with computers in which users search for a keyword or look for a list of entries provided by search engines, LLMs in user generative AI deployments allow users to be more proactive and give instructions/prompts to the conversational agent. While generating rich and long conversations, this new interaction pattern may, however, poses challenges for users in complex information tasks or scenarios where users have to navigate across different tasks or make sense of chatbot outputs. Such challenges may result in information loss, communication breakdown and user dissatisfaction.

Current LLMs operationalized through generative AI tools such as chatbots primarily provide textual information to be encoded in the conversational user interface (CUI) mostly devoid of graphical information (updates on LLMs may offer new features). The pioneer of such chatbots is OpenAI`s ChatGPT that was launched in November 2022. It reached 100 million monthly active users in two months after launch, making it the fastest-growing consumer application in history (Reuters, 2023). In response to growing popularity, human-AI interaction with generative AI chatbots have come out as an emerging area of research (Bozkurt & Sharma, 2024; Bozkurt, 2023). Since their inception, generative AI tools have enabled using AI for various purposes such as personalized learning, as a tutor, mentor, or simulator on a wide array of fields from education to marketing to programming. Despite the increasing use of generative AI, it also poses some challenges. Considering the bulk of information generated by the LLMs in human-AI conversation, human users are at risk of cognitive overload with exploring the chatbot response and storing information in memory and mental context (Suh et al., 2023). Therefore, HCI needs a paradigm shift in user experience with natural language conversations with generative AI chatbots or conversational agents in order to reduce the cognitive overload in human user-AI conversations especially in tasks where users need to synthesize information from different sources. Therefore, this paper discusses how the human-AI interaction could be improved as user generative AI applications are increasingly used and proposes implementing prompt engineering strategies to deal with the challenges of complex information tasks and receive desired responses/output to user queries from conversational agents.

Literature Review

While LLMs can generate human-like conversations with users quite efficiently, they may fall short in contexts where users need to explore and interpret multi-layered information. These shortcomings can be due to the diversity of the information and size of the generated content. In a study conducted by Suh et al. (2023), the researchers investigated how LLMs perform in complex information tasks and proposed a system contributing to the development of new user interfaces with LLMs enabling multilevel exploration and interpretation of information. Suh et al. (2023) argue that complex tasks entail gathering, organizing, and synthesizing information in a nonlinear manner. One has to navigate back and forth to make sense of complex information, but the sequential nature of a linear conversation may not align well with such complex tasks as users may not keep track of the overall information activity. Highly linear structure of user generated AI interfaces leaves the users with lengthy information to be scrolled and encoded. Therefore, the researchers developed a system called Sensecape to mitigate these concerns in complex information tasks with LLMs and evaluated whether Sensecape supports exploration and sensemaking using a within-subject design.

A baseline system and Sensecape was compared on two topics: (1) impact of AI on the future of work, and (2) impact of global warming on economy. To minimize the order bias, the order of the models and topics were counterbalanced, yielding in 4 (2x2) conditions. The analysis of the system usage logs shows that Sensecape participants explored significantly more concepts than when using the Baseline system. In terms of sensemaking, Sensecape participants structured their topic knowledge more hierarchically and revisited information they had previously interacted with compared to using the baseline system. A notable finding is that a great majority of participants used the hierarchy view in Sensecape to organize information and switch between different levels of abstraction, emphasizing the importance of hierarchy view in exploring complex information and making sense of it.

Suh at al. (2023) represents a good combination of researching LLMs in the context of information exploration and sensemaking from a human-factors perspective. The authors have developed a new system that allow for benefiting from complex information tasks with a new interface integrating LLMs and empirically measured how the system contributed to the exploration and sensemaking of complex information tasks. The study is a pertinent example to situate LLMs in a human-factors context.

Another study investigating the impact of user generative chatbot on task management was conducted by Toxtli et al. (2018). Highly flexible workflows that contain team communication, task refinement and tracking provide a multi-layered and nonlinear interaction pattern with coworkers and machines. Increasing use of chatbots have infused into the work patterns of users. For example, they can ask quick questions and request setting up meetings and reminders from the chatbots. The researchers deployed a chatbot called Taskbot in eight different teams that work on 88 distinct tasks in a workplace setting. The taskbot was deployed a week across eight teams ranging from two to five people working closely on the same project. The user interactions with the chatbot were collected and independently coded by two of the authors of the study. It was found that users sent 12 messages to TaskBot and received 54 messages from the bot.

The researchers found seven different interaction patterns with Taskbot. Users treated the Taskbot in a human-like manner, interacting naturally. Almost all users have communicated with the Taskbot as if it was a human at least once. Users also used the Taskbot to assign hierarchical tasks to the other team members. The users also used the bot to support self-communication. For example, they asked the bot to create reminders and meetings for them. Toxtli et al. (2018) appears as a supportive attempt for the integration of chatbots or conversational agents for work that require coordination, synthesis, and collaboration. As most workplace communication takes place amongst teams and entail a smooth communication, this paper provides a good example of how conversational user interfaces could be designed on the premise of LLM-based user generative AI applications.

Vedula et al. (2023) carried out a study to investigate conversation disentanglement performance of two LLM classifiers. Conversations with chatbots may be entangled with multiple threads as humans tend to interact with their interlocutors with different topics/threads in mind. Creating higher quality context becomes crucial as there may appear multiple threads within a conversation for real-world applications such as the conversations between users and virtual assistants. For example, the same user may interact with the virtual assistant on different products in the same conversation (e.g., tech and pet food) or different attributes of the same product can be threaded in the conversation. Current LLM models may not handle the threaded conversations as they need to monitor the multi-thread architecture. Hence it is vital for the system to disentangle the context by levels of granularity and semantic similarity so that the conversation can keep on and result in successful transactions in e-commerce.

The researchers trained two classifiers jointly using a supervised contrastive learning model: an utterance-parent classifier and an utterance-thread classifier. The former learns if the preceding utterance is a parent utterance of the next utterance given a pair of utterances and accounts for the local semantic relationship between conversation utterances, without considering any conversation history. The latter accounts for the whole conversation thread history as context to calculate the semantic relations between a thread and an incoming utterance. Using their model, the researchers conducted experiments on three large, publicly available datasets from the e-commerce domain and evaluated their classifiers based on the standard metric of F1-score. The conversation disentanglement performance was evaluated using three widely used metrics: normalized mutual information (NMI), Shen-F score, and the mean squared error (MSE). The results show that the model outperformed strong baselines from the literature by at least 3% across all datasets on thread disentanglement performance and shows an improvement in the response generation performance which is crucial for natural language tasks such as question answering and response generation.

This study proposes a novel multi-learning framework that has the potential to improve threaded conversations and even evaluated the model on real-world shopping conversations between customers and a commercial voice agent, observing similar improvements in conversation disentanglement and response generation performance. Considering that virtual agents/assistants are likely to be more commonplace with the rise of generative AI, it is vital to boost the performance of multi(threaded) conversations for a smoother user-system interaction. This article forms the ground to specialize in threaded conversation in virtual spoken dialogue systems.

The last study investigating the assistive nature of LLMs on more complex tasks such as multi-step reasoning was conducted by Wu et al. (2022). While LLMs can generate an output for complex tasks, the output may not satisfy the user completely. To increase the performance of LLMs to respond to complex task scenarios, the authors have employed chaining multiple LLM prompts together, which essentially breaks a big task into several smaller sub-tasks by mapping a specific step with a corresponding natural language prompt. The impact of chaining on both task performance and user experience was evaluated using a within-subject user study where 20 participants complete the tasks using both chaining and a standard (non-chaining) user interface with the same LLMs. The results show that chaining the natural language prompts improved the key dimensions of the human-AI experience such as transparency, collaboration, and mental support.

Wu et al. designed an interface that helps users execute LLM chains interactively. 20 users have been exposed to two tasks: peer review writing and personalized flashcard creation in both chain and non-chain conditions. Three data sources were utilized: (1) a seven-point Likert scale to elicit participants` self-perceived experience, (2) interaction logs that captured the human-AI interaction mechanisms and behaviors, and (3) task outcome of peer reviews and flashcards. The results show that chaining led to improved user experience in human-AI interactions and higher quality work meeting the task goals. This work provides a good attempt at improving the efficiency of LLMs in user-AI interactions to perform well on the high complexity tasks. Integration of chaining interface is also a relevant example of how LLMs are increasingly being part of recent user-machine experiences and highlights the significance of pursing the deployment of LLM-based user generative AI interaction patterns in complex task conditions.

Discussion and Recommendations

The preceding section has pointed out that LLMs have brought about new patterns for human-machine interactions owing to the developments in NLP and generative AI. Despite the robust features of LLMs in construing quite effective conversations with users, many real-world tasks can be rather complex and present challenges for LLMs to decipher (Diederich et al., 2022). In addition, the depth and breadth of human mind and the multifaceted nature of the information around human beings pose challenges in benefitting from LLMs in human-AI interactions. The studies underpinning this paper highlight the significance of LLMs as a new catalyst for user-machine interaction and have by and large manipulated either the user experience interface or the underlying LLM to improve the user-AI interaction. The increasing use of LLMs in various domains, including online learning and educational technology, has shown that LLMs will continue to be utilized heavily. In educational settings, LLMs can serve as personalized tutors, mentors, and simulators, providing tailored learning experiences and supporting students in their educational journeys. However, what sets productive use of conversational AI apart is prompt engineering strategies. Prompt engineering is the process of designing and refining prompts (e.g., questions, instructions) to guide AI models, particularly LLMs to get the desired responses/output (Stanford, 2024). Prompting techniques are found to make a difference in the output or response users receive from the machine. For example, it has been noted that longer and more elaborate prompts work better to achieve more specific responses as in the case of Chain-of-Thought (CoT) prompting (Meincke et al., 2024).

While some tasks are straightforward to be dealt with the help of AI, some more complex tasks require a more fine-grained use of AI and prompting strategies to be employed by users. Particularly, complex information tasks—those requiring gathering, organizing, and synthesizing information in a nonlinear manner—pose unique challenges as such tasks often demand flexibility, iterative exploration, and the ability to navigate the complexity of the tasks. In their examination of the critical integration of generative AI in education via a manifesto, Bozkurt et al. (2024) highlighted that while generative AI has the capacity to reduce cognitive load and facilitate mental models to deal with complex information tasks, it should be used cautiously as a blanket acceptance and use of AI may lead to shallow understanding and may reduce the human judgment, intuition, and creativity.

The interaction taking place between the human user and generative AI system shapes the success in prompting. To achieve desired responses, the user may need to go through a process of prompting with attention to the responses in the mutual conversation with the AI model. Bozkurt (2024a) emphasizes the role user prompting plays in gathering full potential of AI with appropriate prompting strategies:

> "The conversation evolves from merely understanding its capabilities to actively shaping its interactions through prompt engineering. This discipline, therefore, represents both an art and a science, emphasizing effective communication with generative AI to harness its full potential. Prompt engineering emerges as an interdisciplinary field of study, providing the know-how that enables these technologies to be used in their true capacity, beyond the know-what understanding that focuses only on generative AI technology. This field is, therefore, crucial for guiding generative AI's performance, revealing its true potential not just in its capabilities but in how we direct those capabilities to achieve desired outcomes." (p. 115).

Prompting is an iterative process entailing a purposeful strategizing for the user to receive accurate, useful, and ethical responses to their queries (OpenAI, 2023). It is critical to employ various strategies leading to well-crafted and high-quality prompts. Therefore, based on the existing literature (e.g., Mollick

& Mollick, 2023; Bozkurt, 2024a) and recommendations from the widely used generative AI platforms (e.g., OpenAI), this paper attempts to offer the following prompting strategies users may employ to interact with the conversational AI tools or LLMs.

1. Provide clear instructions. As LLMs cannot read beings` mind (Webson & Pavlick, 2021), users are expected to leave less chances for the LLMs to guess what they want. There are several ways to help the machine to guess less and understand your goal clearly. To do this, the user can provide details, ask the model to adopt personas, provide examples, and specify the scope of the length of response.
2. Decompose complex tasks into simpler sub-tasks. Complex tasks may tend to result in more errors in reasoning. Therefore, the user may choose to apply prompting techniques that would allow the system to go through intermediate simpler steps to achieve the larger goal. For example, Chain-of-Thought (CoT) prompting could facilitate such complex tasks/queries. CoT is essentially decomposing the problem/task into intermediate reasoning steps that lead to the final answer for the problem/task (Wei et al., 2022). Despite standard prompting, CoT aims to provide not only the answer but also the thought process on how LLM accomplished the complex task reasoning, which is notable to have a more transparent and interpretable, and trustworthy AI response. CoT was found the most successful prompting strategy in Meincke et al.`s (2024) comparison for idea generation and diversity.
3. Identify the audience for whom the output generated by the LLM will be used toward. For example, if the user is likely to send an email to their clients in a corporate setting, the audience should be tailored for the clients. As audience and their characteristics vary extensively, the user needs to identify the audience and tailor the prompt for the audience.
4. Set the genre and the tone. Being specific about the genre (e.g., email, proposal, essay) helps the LLM to produce the type of genre the user needs. Equivocally important is the tone the user wants the machine to apply such as being formal, informal, persuasive and such.
5. Specify the scope in your prompt. A defined scope allows the responses to be focused and targeted to the objective of the task. It also reduces unnecessary iterative refinement, saving time for multi-step complex tasks. It may also increase the usability as specifying the scope, say with bullet points or list, could be more user-friendly. This could also relate to the boundaries and length of output the user seeks for.
6. Assign role or persona. Assigning a specific role to the AI contributes to form a clear context and tailor responses to the task`s unique requirements by narrowing the focus and improving accuracy. A persona is conducive to specialized responses by framing the LLM as an expert in a particular domain. For example, assigning the persona of data analyst would ensure that the response includes the related terminology and technical insights for a data analysis task.

Conclusion and Implications

In conclusion, this paper has explored the transformative impact of Large Language Models (LLMs) on human-computer interaction, particularly through the lens of generative AI chatbots. The introduction highlighted the shift from traditional interaction patterns to natural language user interfaces, foregrounding the role of LLMs in enabling human-like conversations. The literature review provided insights into the challenges and opportunities presented by LLMs in complex information tasks such as task management and multi-step reasoning. Key findings from the reviewed studies encapsulate the hierarchical views for sensemaking in complex tasks, the need for disentangling conversation threads for better context deciphering, and the benefits of chaining prompts for improved task performance and user experience. These findings underscore the need for innovative user interface designs and prompt engineering strategies to enhance the effectiveness of LLM-based interactions. The recommendations section proposed several strategies for prompt engineering, emphasizing the iterative nature of designing effective prompts to guide AI models. By employing these strategies, users can achieve more accurate, useful, and ethical responses from conversational AI tools.

Prompt engineering stands out as a critical generative AI literacy that requires the knowledge powering the AI as well as practical communication skills so that AI model could be guided for the desired output. This brings some implications that could be considered for better use of prompt engineering strategies. For example, as AI is exponentially infusing into our lives and workplace environment, the ability to craft effective prompts becomes a critical skill for both personal and work environments. Second, as complex information tasks entail a non-linear process, there is a need for more intuitive interfaces that allow users to interact more smoothly with the generative AI capabilities. Third, as AI-generated content could be used in decision-making, users should apply prompts that seek for more responsible and ethical use of AI capabilities. Lastly, further studies could assess the effectiveness of the various prompting techniques in real-world scenarios on AI performance and usability. The purpose of this study has been to review the current literature on the complex information tasks in the context of generative AI and offer a critical perspective on the use of prompt engineering strategies while integrating generative AI. While doing so, the findings of the paper does not argue for generalizable findings; it is limited to the interpretation and perspective on the use of generative AI with prompting strategies.

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Author's Contributions (CRediT)

Kadir Karakaya: Conceptualization, methodology, formal analysis, writing—original draft preparation, writing—review and editing. The author has read and agreed to the published version of the manuscript.

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This study is linked to the following SDG(s): Quality education (SDG 4).

Authors` Notes

Based on *Academic Integrity and Transparency in AI-assisted Research and Specification Framework* (Bozkurt, 2024b), the author of this study acknowledges that this paper was edited and refined with the assistance of OpenAI`s ChatGPT and Microsoft Copilot (Versions as of December 2024), complementing the human editorial process. The human author critically assessed and validated the content to maintain academic rigor. The author also assessed and addressed potential biases inherent in the AI-generated content. The final version of the manuscript is the sole responsibility of the human author.

Data Accessibility Statement

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Ethics and Consent

Because this study doesn't involve any living entities, an ethics review is not applicable.

Competing Interests

The author has no competing interests to declare.

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